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Modeling user types changes in gamified systems

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Modelagem de mudanças de perfis de usuário em sistemas gamificados

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This work is dedicated to my parents, José Ferreira and Simone Guimarães, who did enormous efforts to make it possible for me to have formal education, and to my grandfather João Santos (in memoriam), who could never attend school, however, proudly used to say that he had a granddaughter who was a teacher.

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"I've only learned one thing so far: I'll be forever me. All the accidents I believed were inevitable, all those nights that were as long as eternity... You've done your best"

(Kim Namjoon)

RESUMO

SANTOS, A. C. G. **Modelagem de mudanças de perfis de usuário em sistemas gamificados**. 2023. 184 p. Dissertação (Mestrado em Ciências – Ciências de Computação e Matemática Computacional) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos – SP, 2023.

Recentemente a gamificação (isto é, o desenvolvimento de sistemas, serviços e atividades que provêem benefícios motivacionais semelhantes aos que jogos normalmente criam) tem sido aplicada em diferentes domínios buscando criar uma melhor experiência ao usuário. O sucesso da aplicação dessa estratégia, entretanto, se baseia em diferentes aspectos (por exemplo, o perfil do usuário) e em como o design de gamificação é implementado. Apesar de ao longo do tempo diferentes estudos tenham proposto e validado modelos de usuário (por exemplo, Bartle, BrainHex e Hexad) para representar os diferentes perfis de usuário em jogos e ambientes gamificados, pouco se é conhecido acerca de se e como esses perfis de usuário mudam com o tempo e consequentemente influenciam nos resultados de aplicação desses modelos na prática (por exemplo, para personalizar ambientes gamificados). Pensando nesse problema, essa pesquisa visa analisar como os perfis de usuário do modelo Hexad, o modelo mais indicado para personalizar gamificação, pode mudar depois de seis meses da primeira avaliação e como é possível modelar perfis de usuários baseados nessas mudanças. Para atingir esses objetivos, a pesquisa focou em três aspectos: *i)* análise das propriedades psicométricas da escala Hexad em português do Brasil; *ii)* análise da estabilidade dos perfis de usuário do Hexad após seis meses e como o perfil muda a partir da primeira medição; e *iii)* análise do impacto do perfil do Hexad no design de gamificação. Por meio de uma série de estudos, essa pesquisa indicou que os perfis de usuário do Hexad não podem ser considerados estáveis, que estes influenciam o design de gamificação e também influenciam na modelagem do perfil do usuário em sistemas gamificados. Além de indicar uma série de melhorias na versão em português do Brasil da escala do Hexad e em como alguns perfis podem ser mais estáveis que outros, a pesquisa contribui para a comunidade acadêmica e indústria com uma série de recomendações sobre como modelar perfis de usuários em sistemas gamificados, além de indicar possíveis novos estudos que podem ser conduzidos na área de personalização da gamificação.

Palavras-chave: Perfil de usuário, Gamificação, Personalização, Modelagem de usuário.

ABSTRACT

SANTOS, A. C. G. **Modeling user types changes in gamified systems**. 2023. 184 p. Dissertação (Mestrado em Ciências – Ciências de Computação e Matemática Computacional) – Instituto de Ciências Matemáticas e de Computação, Universidade de São Paulo, São Carlos – SP, 2023.

In recent years, gamification (*i.e.*, the design of systems, services, and activities to provide motivation benefits as those games usually create) has been applied in several domains seeking to improve user experience. The success of applying this strategy, however, relies on several aspects (*e.g.*, user profiles) and on how the gamification design is implemented. Even though over the years different studies have proposed and validated user models (*e.g.*, Bartle, BrainHex, and Hexad) to represent the different user profiles in games and gamified settings, little is known about whether and how these user profiles change over time and consequently influences in the results of applying these user models in practice (*e.g.*, to personalize gamified systems). To address this problem, this research aims to analyze how the user types from the Hexad model, the most indicated model to personalize gamification, can change after six months of the first evaluation, and how it is possible to model user profiles based on these changes. To achieve these goals, this research focused on three main aspects: *i)* Analysis of the psychometric properties of the Hexad scale in Brazilian Portuguese; *ii)* Analysis of the stability of the Hexad user types after six months and how the user profile changed based on the first evaluation; and *iii)* analyses of the impact the Hexad user types have on the gamification design. Based on six studies, this research indicated that the profiles from the Hexad model can not be considered stable over time, that they influence the gamification design, and also influence the user profile modeling on gamified systems. Apart from the indication of improvements needed to be made in the Brazilian version of the Hexad scale and that some profiles can be more stable than others, this research contributes to the academics and practitioners with sets of recommendations on how to model user profiles in gamified systems, and with the indication of new studies that can be conducted in the personalized gamification field.

Keywords: User Profile, Gamification, Personalization, User Modeling.

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LIST OF ABBREVIATIONS AND ACRONYMS

AVE	Average Variance Extracted
CFI	Comparative Fit Index
EPC	Expected Parameter Change
GFI	Goodness of Fit Index
HCI	Human-Computer Interaction
NFI	Bentler-Bonett Normed Fit Index
RHO A	Jöreskog's Rho
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Square Residual
TLI	Tucker-Lewis Index

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CHAPTER 1

INTRODUCTION

Over the last decades, video games have become an important source of entertainment for millions of people from different demographic backgrounds (KOIVISTO; HAMARI, 2019). With the advancements in technology and design, video games transposed the line of entertainment, also becoming a source of immersion, education, and social interaction (GUPTA *et al.*, 2021). One reason for this is that video games can engage and positively affect people's behavior (KOIVISTO; HAMARI, 2019; HÖGBERG; HAMARI; WÄSTLUND, 2019; HASSAN *et al.*, 2020). To create in other contexts similar positive experiences, gamification, *i.e.*, the design of systems, services, and activities to provide motivation benefits as those games usually create (KOIVISTO; HAMARI, 2019; HAMARI, 2019), has been widely investigated and applied in the last years (KOIVISTO; HAMARI, 2019; KLOCK *et al.*, 2020; BAI; HEW; HUANG, 2020). Although being a recent research field (BAI; HEW; HUANG, 2020), it has gained popularity through its application in different contexts, such as health (JOHNSON *et al.*, 2016; ORJI; TONDELLO; NACKE, 2018; ALTMEYER *et al.*, 2020a), public administration (HASSAN, 2017; HARVIAINEN; HASSAN, 2019), and sustainable consumption (GUILLEN; HAMARI; QUIST, 2021). Although the use of gamification can be observed in several contexts, the majority of studies have been conducted considering the educational context (KOIVISTO; HAMARI, 2019; KLOCK *et al.*, 2020).

More recently, researchers focused on making analyses of the users' experience in gamified settings considering how the individual experiences of the users could influence the use of these environments, therefore investigating whether and how the gamification works (KOIVISTO; HAMARI, 2019; KLOCK *et al.*, 2020; BAI; HEW; HUANG, 2020). Most of these studies have reported positive results, however, some mixed and even negative results also have been reported (TODA; VALLE; ISOTANI, 2017; KOIVISTO; HAMARI, 2019; KLOCK *et al.*, 2020; BAI; HEW; HUANG, 2020). One of the main hypotheses for these mixed and negative effects is that people have different characteristics and preferences over game elements, which leads to different perceptions regarding the gamification design (LAVOUÉ *et al.*, 2018; HALLIFAX *et* *al.*, 2019b; OLIVEIRA *et al.*, 2020), that can positively or negatively be affected considering the game elements used. At the same time, it is common to develop gamified systems in a way called "one-size-fits-all", which means that the users' preferences are ignored and the designers create a universal gamified environment to suit all users (TONDELLO; ORJI; NACKE, 2017; OLIVEIRA; BITTENCOURT; VASSILEVA, 2018), thus possibly affecting their experience negatively (TONDELLO; ORJI; NACKE, 2017; LAVOUÉ *et al.*, 2018; RODRIGUES *et al.*, 2019).

To personalize gamified settings, researchers and designers have considered distinct characteristics of the user profile as player or user types, gender, age, and personality traits (KLOCK *et al.*, 2020). Nowadays, the player/user typologies (*e.g.*, Bartle (BARTLE, 1996), Yee (YEE, 2006), and Hexad (MARCZEWSKI, 2015)) are the most investigated user characteristic to personalize gamified environments (KLOCK *et al.*, 2020), especially taking into consideration that these typologies consider different aspects of the users, such as behavior in games and intrinsic and extrinsic motivations (HAMARI; TUUNANEN, 2014; MARCZEWSKI, 2015) and its use can influence the success of the personalization (HALLIFAX *et al.*, 2019b). Despite the considerable number of studies about personalization of gamified environments (KLOCK *et al.*, 2020; HALLIFAX; LAVOUÉ; SERNA, 2020), the results are still contradictory, and not always, the user models are faithful to each person's preferences, as well as, not always, personalization has positive effects on the users' experience (KLOCK *et al.*, 2020).

1.1 Motivation and Research Questions

Considering the mixed results of personalizing gamified environments based on player/user typologies, theoretical and exploratory studies started to argue that one possible reason for these results was that the users' preferences may change over time (BUSCH *et al.*, 2016; KLOCK *et al.*, 2020), and thus, players and users typologies would be dynamic. This dynamicity would directly influence the gamification field since the personalization currently made (generally static) would be insufficient to improve the users' experience in the long term, which would require developers and researchers a way to continuously analyze the user types and create a personalization that dynamically changes according to the changing of the users' profile. However, these studies only conducted exploratory analyses of the changes (BUSCH *et al.*, 2016), not allowing gamification designers and researchers to know how these changes occur over time and how to model user profiles based on these changes.

Considering the aforementioned context, it is essential to the field of personalized gamification furthering the knowledge about how the user types can change after the first evaluation and how to model user profiles based on these changes. Therefore, this dissertation has as main research questions:

- **RQ1**: How do the user types changes after the first user type evaluation?

- **RQ2**: How to model user profiles based on the user type changes?

To answer the research questions, we: *i)* conducted an analysis of the psychometric properties of the Hexad scale in Brazilian Portuguese with adults and adolescents, *ii)* identified whether and how the user types changed after six months, *iii)* identified how the user types are related to other user's aspects and preferences for gamification designs, and *iv)* developed a set of recommendations about how to model user profiles in personalized gamified systems.

1.2 Structure

The remaining of this document is organized as follows. Chapter 2 presents the background information on gamification, personalization of gamification, and player/user typologies. It also presents the studies that have indicated that user typologies would change over time. Next, in Chapter 3, Chapter 4, and Chapter 5, we present the studies that sought to answer the research questions of this research. Finally, in Chapter 6 we summarize the advancements and limitations of this research, as well as the papers published or submitted during the study.

CHAPTER

2

LITERATURE REVIEW

This section is organized into four main parts, with three initial parts providing background about gamification, personalization of gamification, and player and user typologies, and the last one providing a review of the studies that have indicated that the player/user types could change over time.

2.1 Gamification

Even though gamification can be considered a recent field and most of the research and practical application had happened in the last decade (KOIVISTO; HAMARI, 2019; KLOCK *et al.*, 2020; BAI; HEW; HUANG, 2020), forms of gamification have been observed in the early 20th century in the Soviet Union and at the end of 20th century in the United States (NELSON, 2012). Over the years, gamification has been defined in different ways and even though it has been documented early before, the 2011's coined definition of gamification as the use of game elements in non-game contexts (DETERDING *et al.*, 2011), has been largely used. After gamification become a trend in many fields (KOIVISTO; HAMARI, 2019; BAI; HEW; HUANG, 2020) and become a well-established technique in Human-Computer Interaction (RAPP *et al.*, 2019), its definition has been updated mainly depending on the context of the application. One of the most recent definitions of gamification is that gamification refers to the act of transforming systems, services, organizations, and activities to provide similar experiences as those games usually provide (HUOTARI; HAMARI, 2017; KOIVISTO; HAMARI, 2019; HAMARI, 2019).

Gamification can be difficult to implement since its design involves the user's motivation and behavior aspects (MORSCHHEUSER *et al.*, 2017) and can be grounded in several theories for example Goal-setting theory, Self-determination theory, and Flow theory (BAI; HEW; HUANG, 2020). Overall, most of the studies about gamification search how gamification can be applied and is perceived and experienced by the users (KOIVISTO; HAMARI, 2019). Even though gamification has been successfully applied to increase user engagement, it has presented mixed users outcomes, a high context dependence, and varied among individuals (TODA; VALLE; ISOTANI, 2017; BÖCKLE; NOVAK; BICK, 2017; KOIVISTO; HAMARI, 2019; ALTMEYER *et al.*, 2021). Recent results identified that, while gamification can foster enthusiasm and fulfill the need for recognition, it also can cause competition, anxiety, and jealousy (KOIVISTO; HAMARI, 2019; BAI; HEW; HUANG, 2020).

Even though the buzz around gamification had produced a large number of studies, more recently researchers started to indicate the need for studies to explore the long-term effects of its application, the relevance of dynamic modeling, as well as the need for further analysis of the relationship between gamification and user's characteristics (BAI; HEW; HUANG, 2020; KLOCK *et al.*, 2020; ALTMEYER *et al.*, 2021), therefore, indicating that the field yet has theoretical and empirical gaps (KOIVISTO; HAMARI, 2019).

2.2 Personalization of gamification

Personalizing gamification, *i.e*, tailoring game design elements according to the user preferences to improve engagement (TONDELLO; NACKE, 2020), is an important aspect of the design of gamification settings considering that people present differences in the perception of game design elements (ALTMEYER *et al.*, 2021). Therefore, personalization seeks to create a personalized environment that is more suitable to the users' needs and preferences (ALTMEYER *et al.*, 2021; KLOCK *et al.*, 2020). Based on this need to personalize gamified environments, researchers and designers started to move towards an understanding of how the game elements would affect the users' reactions (BÖCKLE; NOVAK; BICK, 2017). Most of the studies use self-reported data to investigate how this personalization could be developed (TONDELLO; NACKE, 2020), considering different users' aspects such as gender (CODISH; RAVID, 2017; TODA *et al.*, 2019b; OLIVEIRA; BITTENCOURT, 2019), age (TONDELLO *et al.*, 2019; MORA *et al.*, 2019; ALTMEYER; LESSEL, 2017), player or user type (LAVOUÉ *et al.*, 2018; HALLIFAX; LAVOUÉ; SERNA, 2020) or personality traits (JIA *et al.*, 2016; HALLIFAX *et al.*, 2019b). Prior research also sought to understand how users were motivated in gamified systems by considering different theories, as for example Flow (CSIKSZENTMIHALYI; CSIKZENTMIHALY, 1990) or Self-determination theory (DECI; RYAN, 1985) and considering different outcomes like engagement (HALLIFAX; LAVOUÉ; SERNA, 2020), enjoyment (OLIVEIRA *et al.*, 2022a), and motivation (REYSSIER *et al.*, 2022).

Overall, these studies considering a broad of users' aspects furthered the gamification field when indicating that gender differences exist when applying gamification (CODISH; RAVID, 2017; OLIVEIRA; BITTENCOURT, 2019), that motivation can be improved and demotivation can be decreased by the use of a proper set of game elements (HALLIFAX *et al.*, 2019b; HALLIFAX; LAVOUÉ; SERNA, 2020), as well as that the users' preferences over game elements and gamification designs depend on the player or user type of the user (TONDELLO *et* al., 2019; OLIVEIRA; BITTENCOURT, 2019). More recently, researchers started to point out that some aspects such as context and how a user characteristic can impact other characteristics, should be more investigated (KLOCK *et al.*, 2020).

2.3 Player and user typologies

As aforementioned, users have different motivations and preferences, and therefore, it is necessary to personalize gamified systems to create a more suitable environment for them. This can take considerable effort considering the different characteristics users have. Throughout the years, researchers have worked on how certain characteristics may affect the users while using a gamified system, and therefore, how people could be grouped into player or user types according to these characteristics and motivations (FERRO; WALZ; GREUTER, 2013; YEE, 2006; NACKE; BATEMAN; MANDRYK, 2014). Players and users typologies are used to try to simplify the complexity of the users (SIDEKERSKIENĖ; DAMAŠEVIČIUS; MASKELIŪNAS, 2021; GONZÁLEZ-GONZÁLEZ *et al.*, 2022), and according to Hallifax *et al.* (HALLIFAX *et al.*, 2019b), the choice of the user typology is one of the main factors that can influence the user motivation in personalized gamified environments. Even though studies have proposed different player and user typologies, there is a predominance in the use of Bartle and Hexad's typologies to personalize gamification (KLOCK *et al.*, 2020). The player model presented by Bartle (BARTLE, 1996), was one of the first player type models created to categorize users. His model, developed for game design, proposed a classification of four player types: *i)* Achiever, a player type whose main goals are to earn points and rise levels; *ii)* Explorer, a player type that enjoys exploring the internal machinations of the game; *iii)* Killer, a player type that likes to act on other players and disrupt their player experience; and *iv)* Socializer, a player type that likes to interact with other players (BARTLE, 1996; NACKE; BATEMAN; MANDRYK, 2014; TONDELLO *et al.*, 2019). Even though this player typology has been largely used to personalize gamification (KLOCK *et al.*, 2020), recent studies argued that this player type categorization should not be applied to gamification, considering that this player model was created specifically for game design (TONDELLO *et al.*, 2016; BÖCKLE; NOVAK; BICK, 2017; KLOCK *et al.*, 2020; MARTIN *et al.*, 2021).

Based on Bartle's player types and data collected from Massive Multiplayer Online Role-Playing Games (MMORPGs), Yee (YEE, 2006) proposed an empirical model of player motivations. In his analysis, Yee identified three main dimensions of player motivation: Achievement, with advancement, mechanics, and competition as sub-components; Social with socializing, relationship, and teamwork as sub-components; and Immersion, with discovery, role-playing, customization, and escapism as sub-components (TONDELLO *et al.*, 2016; GONZÁLEZ-GONZÁLEZ *et al.*, 2022). Although this player typology was developed for game design, it has been also applied for gamification (TONDELLO *et al.*, 2016; KLOCK *et al.*, 2020). The model created by Ferro *et al.* (FERRO; WALZ; GREUTER, 2013) was developed based on personality traits and prior player types models, theoretically describing five player types: *i)* Dominant, players that have a strong need to be visible; *ii)* Objectivist, players that like to demonstrate their ability and intelligence; *iii)* Humanist, players that like social engagement; *iv)* Inquisitive, players that enjoy exploring and investigating; and *v)* Creative, players that like to create and develop (TONDELLO *et al.*, 2019; KLOCK *et al.*, 2020). Barata *et al.* (BARATA *et al.*, 2016) proposed a player model to identify students' profiles based on their performance and gaming preferences. Their model categorizes the students into four different player types: *i)* Achiever, students focused on reaching goals and acquiring points; *ii)* Regular, students with performance above the average and equilibrium between achievements and traditional evaluation components; *iii)* Halfhearted, students that performed below the average; and *iv)* Underachiever, students with the lowest performance (KLOCK *et al.*, 2020). Also based on different player typologies, Borges *et al.* (BORGES *et al.*, 2016) proposed a model with five player roles: *i)* Achievers, players who like winning and accumulating rewards; Conquerors, players that appreciate testing their skills competing against other players; *ii)* Creators, players who like customizing the system; *iii)* Explorers, players who enjoy exploring the system; and *iv)* Humanists, players who enjoy socializing with others (KLOCK *et al.*, 2020).

Another player type model that has been used in research to personalize gamification is the BrainHex Model (NACKE; BATEMAN; MANDRYK, 2014), which was created based on prior player typologies, patterns of play, game emotions, and neurobiological findings (NACKE; BATEMAN; MANDRYK, 2014). This player typology has seven player types: *i)* Seeker, a player type that is curious and likes to explore; *ii)* Survivor, a player type that enjoys the intensity of the experience associated with terror; *iii)* Daredevil a player type that likes the excitement of risk-taking; *iv)* Mastermind, a player type that enjoys solving puzzles and creating strategies; *v)* Conqueror, a player type that enjoys difficult tasks and finds satisfaction in beating other players; *vi)* Socialiser, a player type that likes to interact with other people; and *vii)* Achiever, a player type that is motivated by long-term achievements (NACKE; BATEMAN; MANDRYK, 2014). Each player type from the BrainHex model is considered an archetype that typifies a particular player experience (NACKE; BATEMAN; MANDRYK, 2014). Similar to the typologies created by Bartle (BARTLE, 1996) and Yee (YEE, 2006), the BrainHex typology was developed as a player typology for game design, however, it has been used in the gamification field (HALLIFAX *et al.*, 2019b).

To create a specific user typology for the field of gamification, Marczewski developed the Gamification User Types Hexad (MARCZEWSKI, 2015). This user typology was developed based on the Self-determination theory (SDT), which indicates that people are intrinsically motivated when the activity supports three basic human psychological needs (*i.e.*, competence, autonomy, and relatedness), or extrinsically motivated when the reason for doing something is not an interest in the activity itself (DECI; RYAN, 1985). Based on this concept of intrinsic and extrinsic motivation, the Hexad model proposes six user types: *i)* Philanthropists, a user type that is motivated by purpose; *ii)* Socialisers, a user type that is motivated by relatedness; *iii)* Free

Spirits a user type that is motivated by autonomy; *iv)* Achievers, a user type that is motivated by competence; *v)* Players, a user type that is motivated by extrinsic rewards; and *vi)* Disruptors, a user type that is motivated by the triggering of change. In the Hexad, although the users present a dominant user type (*i.e.*, the strongest tendency (HALLIFAX *et al.*, 2019b)) they are motivated by all the other user types in some degree (TONDELLO *et al.*, 2016). The Hexad has been largely used in the gamification field since it is considered the most appropriate user typology for personalization (HALLIFAX *et al.*, 2019b), has an evaluated scale to measure the user types in different languages (TONDELLO *et al.*, 2019; TASKIN; ÇAKMAK, 2020; OOGE *et al.*, 2020; MANZANO-LEÓN *et al.*, 2020; KRATH; KORFLESCH, 2021), and has been successfully used in studies from different contexts (ORJI; TONDELLO; NACKE, 2018; LOPEZ; TUCKER, 2019; MORA *et al.*, 2019; ALTMEYER *et al.*, 2020a; HALLIFAX; LAVOUÉ; SERNA, 2020).

Considering all these typologies, it is possible to identify certain shared types, as most of them have user profiles that reflect characteristics of seeking for achievement (*i.e*, Achiever from Bartle, BrainHex, Hexad, and Barata's model), exploration (*i.e*, Inquisitive from Ferro, Seeker from Brainhex, and Free Spirit from Hexad) or socialization (*i.e*, Socializer/Socialiser from Bartle, BrainHex, and Hexad or Humanist from Ferro and Borges' models). To investigate the game elements that would better suit each user type, researchers often select them from prior studies (MONTERRAT; LAVOUÉ; GEORGE, 2017; LAVOUÉ *et al.*, 2018; DAGHESTANI *et al.*, 2020), the most used in literature (OLIVEIRA; BITTENCOURT, 2019; HALLIFAX; LAVOUÉ; SERNA, 2020), or from suggestions from the creators of the typology (GIL; CANTADOR; MARCZEWSKI, 2015; TONDELLO *et al.*, 2016). Also, it is common to analyze the relationship between the user types and game elements individually, with few studies trying to relate the user types with specific sets of game elements (TONDELLO *et al.*, 2016).

The studies that have applied player and user typologies to personalize gamification have reported that different player types have different preferences and perceptions for game elements and gamification designs (TONDELLO *et al.*, 2016; MONTERRAT; LAVOUÉ; GEORGE, 2017; OLIVEIRA; BITTENCOURT, 2019) and also that users can become more engaged when interacting with game elements tailored specifically for their user types (HALLIFAX; LAVOUÉ; SERNA, 2020). Even though the players and user typologies are nowadays the most used characteristic to personalize gamification, studies have reported that only the dominant user profile is not sufficient to discriminate users' preferences over game elements (HALLIFAX *et al.*, 2019b), as well as that user types can not be considered stable over time (BARTLE, 1996; BUSCH *et al.*, 2016; YILDIRIM; ÖZDENER, 2021).

2.4 Do people's player and user types change over time?

Even though the personalization of gamification design has been indicated as an important issue in the gamification field and most of the studies relied on the player or user typologies to personalize gamified settings (KLOCK *et al.*, 2020), only a few studies have sought to identify whether the player or user types could be considered stable over time. One of the pioneers in the definition of player typologies, Bartle (BARTLE, 1996) theoretically indicated in his study that the player types should not be considered stable. He pointed out that, even though the players could be located in one specific player type, they could change their interest freely and change to another player type (BARTLE, 1996). Using the BrainHex Model (NACKE; BATEMAN; MANDRYK, 2014), Busch *et al.* (BUSCH *et al.*, 2016) conducted two online studies to confirm the validity of the BrainHex scale and also analyze whether the respondents' player types were the same after six months. The study results demonstrated that the player types of the respondents when using the BrainHex scale (NACKE; BATEMAN; MANDRYK, 2014), could not be considered stable over time. Even though their results demonstrated the changes, similar to Bartle (BARTLE, 1996) they considered a game-based player typology, which results might not be the same when considering the context of gamification. They also did not present further analyses about how the changes would happen over time and how to model user profiles based on these changes.

Evaluating the stability of the Hexad model, Yildirim and Ozdener (YILDIRIM; ÖZDENER, 2021) conducted an exploratory study with 66 participants, where they evaluated whether the Hexad user types of teacher candidates in a University in Turkey would change after 16 months. They also conducted descriptive statistics and correlation analysis, finding results that indicated that the dominant user type of the participants changed over time. Furthermore, their results demonstrated that the average scores of the sub-scales presented moderate similarities, with the Philanthropists sub-scale presenting the most significant change. Even though this study's results indicated that the user type is not stable over time, they did not further explore the changes or indicated how it would be possible to model user profiles based on these changes. Table 1 presents a comparison between the related works.

Table 1 – Related works comparison

Study	**Model**	**P**	**Context**	**Domain**
Bartle (BARTLE, 1996)	Bartle	-	Games	General
Busch *et al.* (BUSCH *et al.*, 2016)	BrainHex	243	Games	General
Yildirim and Ozdener (YILDIRIM; ÖZDENER, 2021)	Hexad	66	Gamification	Education
Key: Model: player/user typology; P: number of participants.				

Source: Elaborated by the author.

2.5 Final Considerations

This chapter presents an overview of gamification and its personalization. Even though the literature on gamification highlights the importance of personalization and that it is mostly made based on player or user typologies, prior research about user changes in this type of system only focused on measuring whether they change without exploring more about how the user types change. In this context, our research was developed in order to conduct further analyses of how the user types change over time and how it would be possible to model user profiles in gamified systems based on the changes. For this purpose, we used the Hexad Gamification User types, a typology created for the gamification field, and analyzed the users' types in two different time moments. We also related the user types with other user aspects and habits, in order to develop a set of recommendations on how to personalize gamification based on the user types.

CHAPTER

3

THE HEXAD USER TYPES SCALE: PSYCHOMETRIC PROPERTIES OF THE BRAZILIAN VERSION

This subsection presents the studies conducted with the goal of analyzing the psychometric proprieties of the gamification Hexad scale in Brazilian Portuguese. Initially, we conducted a study with a sample composed in majority by adults, and then another study only with adolescents (aged between 13 to 16). Scales to measure the users' profiles are essential to the field of personalized gamification, however, the Hexad scale was not evaluated in several widely spoken languages, including Brazilian Portuguese. The first study (see Appendix C) has been published as a full paper in Scientific Reports in March, 2022 (SANTOS *et al.*, 2022), and the second study is under review in the same journal.

3.1 Psychometric investigation of the Hexad scale in Brazilian Portuguese

The Hexad user types scale (composed of 24 non-invasive items) to evaluate user types was initially created in English (TONDELLO *et al.*, 2016), and since its development, has been validated in different languages (TASKIN; ÇAKMAK, 2020; OOGE *et al.*, 2020; MANZANO-LEÓN *et al.*, 2020; KRATH; KORFLESCH, 2021). Although these validation studies provided different versions of the scale, missing validated translations of the instrument prevent its use among other non-native speakers. As a consequence, albeit its proven scientific and practical value, researchers and practitioners in many countries cannot make use of the Hexad scale. In the study to validate the scale in English and Spanish, Tondello *et al.* (TONDELLO *et al.*, 2019) tried to validate the scale in Brazilian Portuguese, however, they did not collect enough answers to conduct statistical analyses. We contributed to this issue by conducting a study to analyze the psychometric properties of the Hexad scale in Brazilian Portuguese, a language spoken by more than 211 million native speakers, of which only 5,1% of the population have good English comprehension skills (COUNCIL, 2014). Consequently, we enable researchers to both recruit from a larger and thus potentially more representative pool of participants as well as increase the scientific validity of studies incorporating the Hexad scale in this language.

3.1.1 Method, data collection and participants

To collect the data for this study, we employed an online survey through the platform Google Forms, consisting of two sections: (i) demographic data (age, gender (options were: male, female, other, and I prefer to not inform), educational level, state (options were the 26 Brazilian states and the Federal District)), and gaming habits (if the respondent play games and the frequency (options were: every day, every week, rarely, and I do not know)), and (ii) the Hexad scale (composed of 24 statements, four items for each sub-scale). The Hexad scale items were randomly presented on a 7-point Likert scale (LIKERT, 1932), as recommended in the original study (TONDELLO *et al.*, 2019). The 24 items of the Hexad scale were the items available (in Portuguese) on the website of the HCI Games Group (HCI, 2016). According to Tondello *et al.* (TONDELLO *et al.*, 2019), two independent native speakers separately translated all the statements and descriptions into Brazilian Portuguese from the original version. Besides, each item was compared and assessed by an independent third native speaker. We also included an "attention-check" statement in the middle of the second section, to check if people were paying due attention when reading and answering the form. Responses from people who missed the attention-check statement were removed from the data analysis.

Aiming to have participants with different backgrounds, participants were recruited via email lists (academic and non-academic) and social networks (Facebook, Instagram, and Twitter). The propagation through Twitter, Facebook, and Instagram was made on personal accounts, and in the propagation on Facebook, the survey was also posted in public groups about gamification. All the postings were not targeted at any kind of ads and the publications were made public to facilitate the propagation by others. Considering that volunteers might be more willing to pay attention in surveys and also without pressure to maximize time usage (TONDELLO; NACKE, 2020), participation in the study was entirely voluntary. Participants had to accept to participate by checking a consent term, where they were informed about the purpose of the study, the study confidentiality, that the data collected would be used in scientific studies, and also the contact of the researchers and universities involved in the study. Participants could quit the study at any time before submitting responses.

We were able to collect 463 responses, of which 42 were discarded for having missed the attention-check item. With that, we analyzed data from 421 participants (219 self-reported as women, 198 self-reported as men, two participants preferred not to provide their gender, and two reported themselves as "other"). We received responses from 23 Brazilian states and the Federal

District, covering the five geographic regions of Brazil. Most of the respondents had at least a bachelor degree (Elementary/Middle/High School = 10%; Bachelor = 32%; Specialized/MBA Courses = 21%; M.Sc. = 24%; Ph.D. = 13%), were older than 20 years (10 to 19 = 9%; 20 to 29 = 29%; 30 to 39 = 28%; 40 to 49 = 23%; 50 to 59 = 10%; over 60 = 1%) and also, most of the respondents (68%) reported that playing games was a habit. Therefore, we were able to collect data from people with different demographic backgrounds.

3.1.2 Results

To analyze the properties of the Hexad scale in Brazilian Portuguese, we analyzed the *i)* descriptive statistics, *ii)* internal reliability, *iii)* correlation between user types, and *iv)* factor analysis of the data. Similar to Manzano-León *et al.* (MANZANO-LEÓN *et al.*, 2020), we also conducted Multi-group Confirmatory Factor Analysis aiming to analyze gender invariance (*i.e.*, to assess whether the survey is understood in the same way by men and women).

Initially, we analyzed the distributions of the responses for all variables by using Kolmogorov–Smirnov test (MASSEY, 1951), which results showed that the scores from all the variables were not normally distributed. We also measured the descriptive statistics (Mean, the standard deviation, and the data variances in each sub-scale), the internal reliability analyses (Cronbach's α), as well as the bivariate correlation coefficients (using Kendall's τ). Table 2 presents the results. Considering that each Hexad sub-scale has four items rated on a 7-point Likert-scale, the minimum value a sub-scale can be is 4 and the maximum value a sub-scale can be is 28. Overall, the reliability scores were acceptable ($\alpha \geq 0.70$), except for the Disruptor sub-scale. Prior studies (TONDELLO *et al.*, 2019; OOGE *et al.*, 2020) have also found similar results ($\alpha \leq 0.70$) for the Disruptor sub-scale. Since the user type scores were non-parametric, as recommended by Wohlin *et al.* (WOHLIN *et al.*, 2012), we measured the bivariate correlation coefficients between each Hexad user type using Kendall's τ. In our study, similar to Tondello *et al.* (TONDELLO *et al.*, 2019), we identified a partial overlap between the user types, however at different levels.

Table 2 – Mean, standard deviation, data variances, internal reliability, and correlations (SANTOS *et al.*, 2022)

UT	M	SD	Var	α	A	*P-value*	D	*P-value*	F	*P-value*	P	*P-value*	R	*P-value*
A	23.90	4.733	22.401	0.871										
D	14.77	5.274	27.811	0.669	0.186**	0.000								
F	22.52	4.614	21.288	0.748	0.424**	0.000	0.310**	0.000						
P	24.18	4.681	21.909	0.885	0.464**	0.000	0.099**	0.005	0.372**	0.000				
R	20.63	5.572	31.052	0.812	0.377**	0.000	0.229**	0.000	0.337**	0.000	0.216**	0.000		
S	20.57	5.690	32.378	0.882	0.338**	0.000	0.087*	0.012	0.300**	0.000	0.483**	0.000	0.271**	0.000

Key: UT: User type; M: mean score; SD: standard deviation; Var: Variance; α: Cronbach's Alpha; A: Achiever; D: Disruptor; F: Free Spirit; P: Philanthropist; R: Player; S: Socialiser. ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

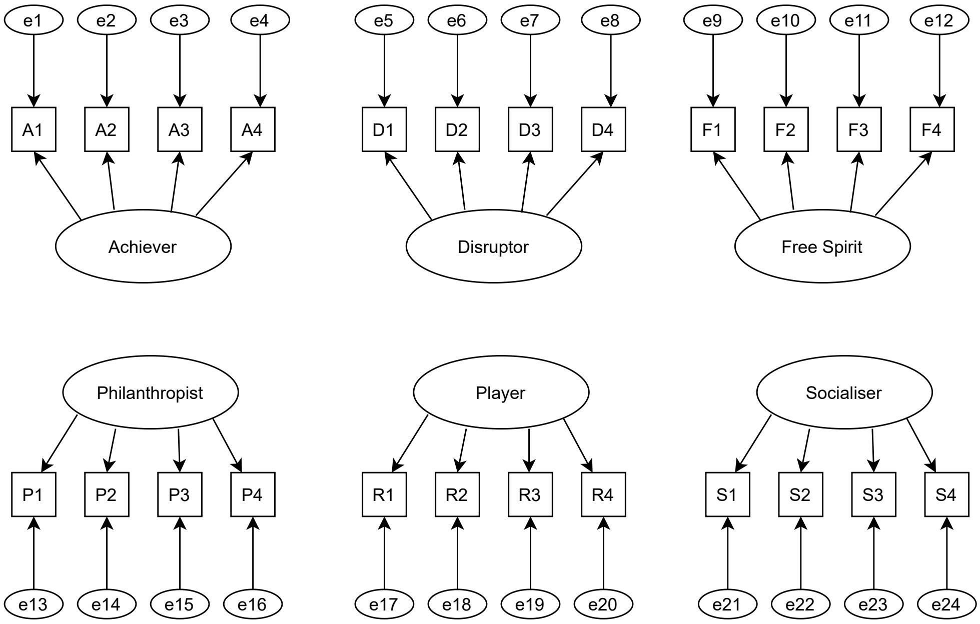
As reported in Table 2, the higher average scores were from Philanthropists, Achievers, and Free Spirits, and the lower average scores were from Disruptors. These values are similar to other recent studies about the Hexad user types (TONDELLO *et al.*, 2019; MANZANO-LEÓN *et al.*, 2020; TASKIN; ÇAKMAK, 2020; ALTMEYER *et al.*, 2020b). We also calculated the dominant user types (*i.e.* the strongest tendency of the respondents (HALLIFAX *et al.*, 2019b)), which distribution results were: Philanthropist = 34%, Achiever = 30%, Free Spirit = 13%, Player = 12%, Socialiser = 11%, and Disruptor = 1%. Philanthropists, Achievers, and Free Spirits were the dominant user types of 77% of the respondents, which was expected considering that the respondents presented higher average scores in these three user types. When considering gender, the distribution of the participants who self-reported as female was: Philanthropist = 35%, Achiever = 26%, Free Spirit = 14%, Player = 10%, Socialiser = 13%, and Disruptor = 1%, while the distribution of the participants who self-reported as male was Philanthropist = 32%, Achiever = 35%, Free Spirit = 10%, Player = 14%, Socialiser = 8%, and Disruptor = 1%. Therefore, there were more Philanthropists, Free Spirits, and Socialisers among the self-reported women, while the self-reported men presented a higher percentage of Achievers and Players as dominant user types.

After this initial analysis, we conducted the confirmatory factor analysis of the data. Considering that prior studies about the Hexad scale employed two different approaches in the conduction of the Confirmatory Factor Analysis, we conducted two different Confirmatory Factor Analyses. While the studies conducted by Tondello *et al.* (TONDELLO *et al.*, 2019) and by Ooge *et al.* (OOGE *et al.*, 2020) considered the Hexad as an orthogonal model (*i.e.*, the six user types as factors without correlation between them), Akgün and Topal (AKGÜN; TOPAL, 2018), Taşkın and Çakmak (TASKIN; ÇAKMAK, 2020), and Manzano-León *et al.* (MANZANO-LEÓN *et al.*, 2020) considered the Hexad model as an oblique model (*i.e.*, the six user types as factors correlated to each other). Initially, we replicated the Confirmatory Factor Analysis conducted by Tondello *et al.* (TONDELLO *et al.*, 2019) and Ooge *et al.* (OOGE *et al.*, 2020), *i.e.*, considering the six user types as factors without correlation between them. Figure 1 presents the path model of this analysis.

To evaluate the goodness of fit of the model, we used the chi-squared test (χ^2), the chi-squared divided by its degrees of freedom (χ^2/df), and the Root Mean Square Error of Approximation (RMSEA). The Chi-squared test did not support the evidence for a good model fit (χ^2_{252} = 1910.204, $p \leq 0.001$). Thus, we calculated the χ^2/df = 3.6, which also did not indicate a good model fit, however, indicated a fair fit (WHEATON *et al.*, 1977; HOOPER; COUGHLAN; MULLEN, 2008). The RMSEA = 0,125 (CI = [0.120, 0.130]) also did not support the evidence for a well-accepted fitted model (HU; BENTLER, 1999). The Comparative Fit Index (CFI) = 0.702, the Tucker-Lewis Index (TLI) = 0.673, the Bentler-Bonett Normed Fit Index (NFI) = 0.673, and the Standardized Root Mean Square Residual (SRMR) = 0.314 also did not indicate an acceptable fit of the model (HU; BENTLER, 1999; HOOPER; COUGHLAN; MULLEN, 2008). However, the Goodness of Fit Index (GFI) = 0.956 indicated a good fit (HAYASHI; BENTLER; YUAN, 2011).

Table 3 presents the factor loadings for each of the Hexad survey items in Brazilian

Figure 1 – Path model of the first confirmatory factor analysis (SANTOS *et al.*, 2022)



Portuguese. Based on these factor loadings, we calculated the composite reliability finding acceptable values (CR $\geq$ 0.7) for all the factors except the Disruptor (Achiever = 0.874; Disruptor = 0.669; Free Spirit = 0.766; Philanthropist = 0.888; Player = 0.818; and Socialiser = 0.886).

In Table 4 we present the modification indices with values that were higher than 30.000. The modification index is an approximation of how much each parameter could decrease the χ^2 value, and therefore, improve the fit model if freely estimated (BROWN, 2015; KLINE, 2015). The Expected Parameter Change (EPC) indicates an estimation of how much the parameter would change if freely estimated (BROWN, 2015). The results indicated that especially item D2 has presented a correlation with all the factors, which indicates that possibly an improvement in this item would improve the model fit.

In summary, when using a similar path model that Tondello *et al.* (TONDELLO *et al.*, 2019) and Ooge *et al.* (OOGE *et al.*, 2020) studies used, confirmatory factor analysis demonstrated that the measurement model has not an acceptable fit considering our data, indicating that some items could be improved. One of the possible explanations for this result is that probably occurred an overlap of items measuring the same factor. The results demonstrated that items D2 and F2 were the weaker fit to their respective sub-scales (see Table 3).

The second confirmatory factor analysis replicated the analysis conducted by Akgün and Topal (AKGÜN; TOPAL, 2018), Taşkın and Çakmak (TASKIN; ÇAKMAK, 2020), and Manzano-León *et al.* (MANZANO-LEÓN *et al.*, 2020). Figure 2 presents the path model of this analysis.

The Chi-squared test did not support the evidence for a good model fit (χ^2_{252} = 646.836,

Table 3 – Factor loadings of the first confirmatory factor analysis (SANTOS *et al.*, 2022)

UT	I	SE	Z-value	CI 5%	CI 95%	λ
A	**A1**	0.087	12.141	0.884	1.225	**0.836**
	A2	0.077	15.827	1.075	1.378	**0.790**
	A3	0.089	11.866	0.879	1.227	**0.779**
	A4	0.086	12.574	0.912	1.248	**0.779**
D	**D1**	0.105	9.822	0.825	1.237	**0.539**
	D2	0.109	7.890	0.645	1.072	0.491
	D3	0.106	11.758	1.035	1.449	**0.648**
	D4	0.099	11.950	0.985	1.371	**0.636**
F	**F1**	0.092	12.509	0.969	1.329	**0.793**
	F2	0.095	8.582	0.629	1.001	0.496
	F3	0.090	12.100	0.914	1.268	**0.807**
	F4	0.098	9.450	0.731	1.113	**0.560**
P	**P1**	0.081	13.543	0.940	1.258	**0.868**
	P2	0.073	16.172	1.042	1.329	**0.851**
	P3	0.083	13.072	0.926	1.252	**0.799**
	P4	0.089	11.585	0.856	1.205	**0.737**
R	**R1**	0.086	15.317	1.145	1.481	**0.694**
	R2	0.075	18.568	1.240	1.533	**0.855**
	R3	0.088	11.556	0.846	1.192	**0.640**
	R4	0.089	14.663	1.131	1.480	**0.712**
S	**S1**	0.069	19.810	1.224	1.493	**0.823**
	S2	0.063	23.211	1.332	1.577	**0.908**
	S3	0.075	16.355	1.087	1.382	**0.721**
	S4	0.068	19.214	1.165	1.430	**0.789**

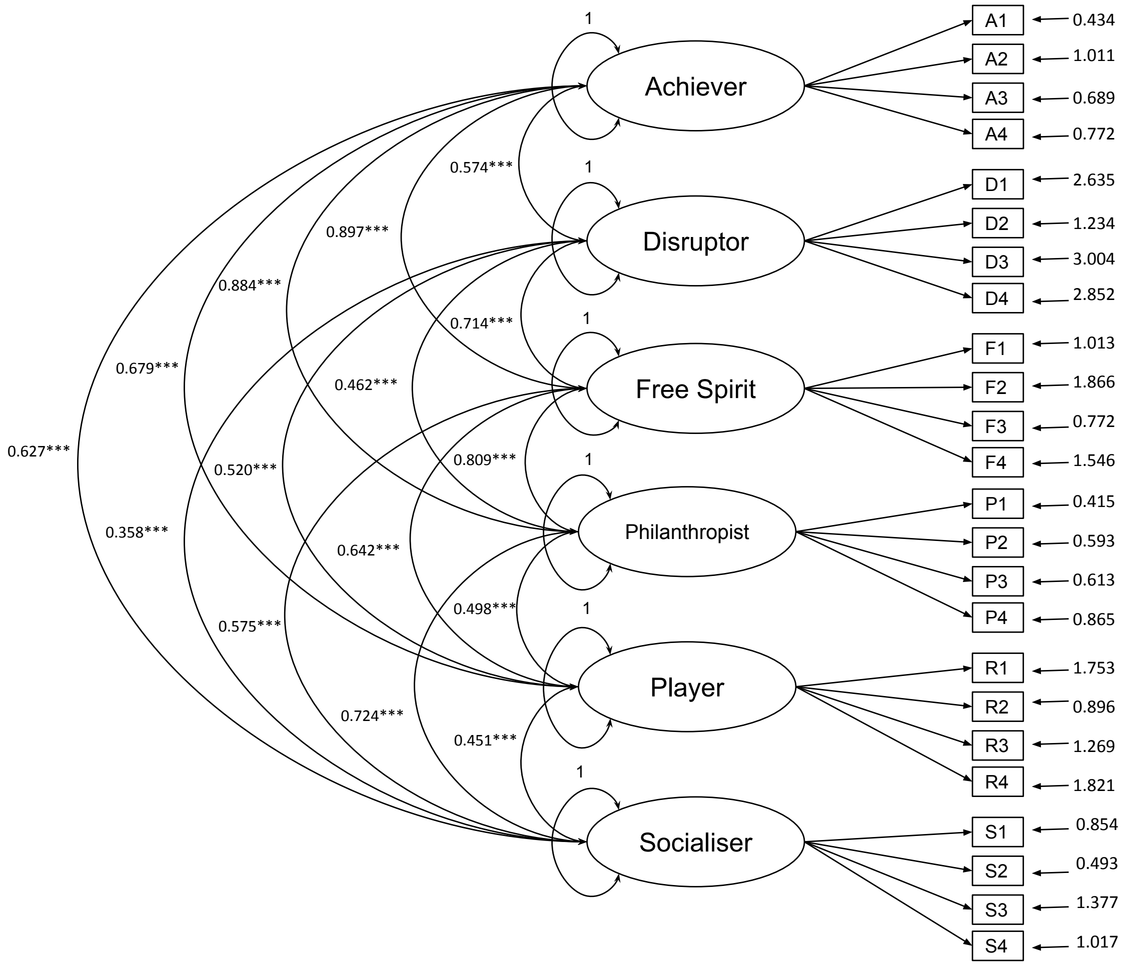
Key: UT: User types/factors; I: Items; SE: standard errors; CR: critical ratios; CI: Confidence interval; λ: standardized λ; bold: $\lambda \geq 0.500$; A: Achiever; D: Disruptor; F: Free Spirit; P: Philanthropist; R: Player; S: Socialiser.

$p \leq 0.001$), however, different from the first confirmatory factor analysis, the χ^2/df = 2.56, the Root Mean Square Error of Approximation (RMSEA) = 0.064 (CI = [0.058, 0.070]), and Standardized root mean square residual (SRMR) = 0.073, indicated a good fit (HOOPER; COUGHLAN; MULLEN, 2008). The Comparative Fit Index (CFI) = 0.926, the Tucker-Lewis Index (TLI) = 0.914, the Bentler-Bonett Normed Fit Index (NFI) = 0.889, and the Goodness of fit index (GFI) = 0.882 were slightly below the acceptable values that would indicate a good fit (HU; BENTLER, 1999; HOOPER; COUGHLAN; MULLEN, 2008). Thus, even though some of the indices did not indicate the good fit of the model to our data when considering the Hexad as an oblique model, the indices were closer to indicating a good fit model than in the first confirmatory factor analysis. Table 5 presents the factor loadings from this second confirmatory factor analysis. We also calculated the composite reliability (CR) based on these factor loadings, finding acceptable values (CR $\geq$ 0.7) for all the factors except the Disruptor (Achiever = 0.873;

Table 4 – Modification indices of the first confirmatory factor analysis (SANTOS *et al.*, 2022)

	Modification Indices	**Expected Parameter Change**
Achiever → D2	111.430	0.884
Free Spirit → D2	98.619	0.864
Philanthropist → D2	88.796	0.781
Free Spirit → R3	76.296	0.613
Socialiser → D2	62.360	0.651
Socialiser → F4	49.211	0.512
Philanthropist → R3	47.072	0.458
Achiever → R3	46.979	0.463
Player → D2	37.588	0.524
Philanthropist → A1	35.505	0.252

Figure 2 – Path model with correlations between the factors (SANTOS *et al.*, 2022)



Disruptor = 0.622; Free Spirit = 0.769; Philanthropist = 0.888; Player = 0.819; and Socialiser = 0.886).

In Table 6 we present the modification indices with values that were higher than 30.000. Again, item D2 presented a correlation with most of the factors, however, in this analysis, items D3 and D4 also presented some correlations with the factors. This might indicate the necessity

Table 5 – Factor loadings of the second confirmatory factor analysis (SANTOS *et al.*, 2022)

				CI		
UT	**I**	**SE**	**Z-value**	**5%**	**95%**	λ
A	**A1**	0.081	13.273	0.918	1.235	**0.853**
	A2	0.076	15.548	1034	1.332	**0.762**
	A3	0.084	12.735	0.902	1.230	**0.789**
	A4	0.081	13.313	0.915	1.231	**0.774**
D	**D1**	0.090	11.228	0.835	1.188	**0.529**
	D2	0.094	14.431	1.169	1.537	**0.773**
	D3	0.107	7.602	0.606	1.027	0.426
	D4	0.105	7.252	0.554	0.965	0.410
F	**F1**	0.087	12.030	0.873	1.213	**0.719**
	F2	0.084	10.891	0.747	1.074	**0.555**
	F3	0.086	11.887	0.858	1.197	**0.760**
	F4	0.072	14.995	0.936	1.218	**0.655**
P	**P1**	0.082	13.322	0.929	1.249	**0.861**
	P2	0.072	16.070	1.020	1.303	**0.833**
	P3	0.080	13.969	0.959	1.272	**0.818**
	P4	0.086	12.099	0.875	1.213	**0.747**
R	**R1**	0.081	16.783	1.193	1.509	**0.714**
	R2	0.066	19.851	1.186	1.446	**0.812**
	R3	0.083	13.559	0.964	1.290	**0.707**
	R4	0.085	14.536	1.073	1.407	**0.677**
S	**S1**	0.067	20.386	1.238	1.501	**0.829**
	S2	0.061	23.679	1.321	1.560	**0.899**
	S3	0.074	16.921	1.102	1.390	**0.728**
	S4	0.067	19.376	1.167	1.429	**0.790**

Key: UT: User types/factors; I: Items; SE: standard errors; CR: critical ratios; CI: Confidence interval; λ: standardized λ; bold: $\lambda \geq 0.500$; A: Achiever; D: Disruptor; F: Free Spirit; P: Philanthropist; R: Player; S: Socialiser.

of improvement in all the Disruptor sub-scale items.

When modeling the path model similar to Akgün and Topal (AKGÜN; TOPAL, 2018), Taşkın and Çakmak (TASKIN; ÇAKMAK, 2020), and Manzano-León *et al.* (MANZANO-LEÓN *et al.*, 2020) studies, the confirmatory factor analysis results demonstrated that the model is closer to an acceptable fit but also can be improved. In this analysis, the items D3 and D4 were the weaker fit to the Disruptor sub-scale (see Table 5). After this confirmatory factor analysis and also considering the analyses made by Akgün and Topal (AKGÜN; TOPAL, 2018), Taşkın and Çakmak (TASKIN; ÇAKMAK, 2020), and Manzano-León *et al.* (MANZANO-LEÓN *et al.*, 2020) studies, we understand that the Hexad is an oblique model, and that is why it presents a better fit model when correlating the items in the confirmatory factor analysis.

To measure gender invariance, we carried out two Multi-group Confirmatory Factor

Table 6 – Second modification indices of the second confirmatory factor analysis (SANTOS *et al.*, 2022)

	Modification Indices	Expected Parameter Change
Free Spirit → D2	106.398	2.348
Achiever → D2	88.736	1.508
Philanthropist → D2	77.717	1.133
Free Spirit → R3	69.735	0.837
Achiever → R3	49.527	0.710
Socialiser → D2	43.896	0.738
Philanthropist → R3	41.049	0.515
Achiever → D4	39.436	-0.801
Philanthropist → D4	34.883	-0.655
Achiever → D3	32.154	-0.749
Free Spirit → D4	31.378	-0.928

Analyses (one considering the orthogonal model and another considering the oblique model). In the first Multi-group Confirmatory Factor Analysis (orthogonal model), the comparisons between the unconstrained model (RMSEA = 0.130 [0.124 - 0.135]; SRMR = 0.321; TLI = 0.655; CFI = 0.685), the metric invariance (RMSEA = 0.128 [0.122 - 0.133]; SRMR = 0.321; TLI = 0.666; CFI = 0.684; Δ CFI = -0.001), and the scalar invariance (RMSEA = 0.127 [0.121 - 0.132]; SRMR = 0.309; TLI = 0.671; CFI = 0.678; Δ CFI = -0.006), indicated an acceptable invariance (ΔCFI $\leq$ 0.01).

In the second Multi-group Confirmatory Factor Analysis (oblique model), the comparisons between the unconstrained model (RMSEA = 0.123 [0.118 - 0.129]; SRMR = 0.097; TLI = 0.688; CFI = 0.715), the metric invariance (RMSEA = 0.121 [0.116 - 0.126]; SRMR = 0.103; TLI = 0.700; CFI = 0.684; Δ CFI = -0.001), and the scalar invariance (RMSEA = 0.120 [0.115 - 0.125]; SRMR = 0.101; TLI = 0.705; CFI = 0.706; Δ CFI = -0.008) also indicated an acceptable invariance (ΔCFI $\leq$ 0.01). Therefore, the results of both Multi-group Confirmatory Factor Analyses demonstrated that the instrument in Brazilian Portuguese can be used regardless of gender and independent of the model.

3.1.3 Discussion

Considering the distribution of the scores, our results were similar to prior research (TONDELLO *et al.*, 2019; MANZANO-LEÓN *et al.*, 2020; TASKIN; ÇAKMAK, 2020; ALTMEYER *et al.*, 2020b), demonstrating that Philanthropists, Achievers, and Free Spirits are the strongest tendencies of the users regarding the Hexad user types, while Disruptor is the lower tendency. We also calculated the dominant user types, indicating that Achievers and Philanthropists were responsible for more than 60% of the dominant user types of the respondents. Partially similar to the results found by Tondello *et al.* (TONDELLO *et al.*, 2019), participants who self-reported as women, seemed to be more motivated by the Philanthropist, Free Spirit, and Socialiser tendencies while participants who self-reported as men, seemed to be more motivated by the Achiever and Player tendencies. The results from the study conducted by Oyibo *et al.* (OYIBO; ORJI; VASSILEVA, 2017), which indicated that men are more responsive to rewards strategies, might explain why men are more motivated by the Player user type.

Our results presented significant correlations between the user types, which some were expected taking into account that their underlying motivations are related (TONDELLO *et al.*, 2016). The strongest correlation occurred between Philanthropists and Socialisers and could be expected since both user types are interested in social interaction, with Socialisers interested in the interaction itself and Philanthropists interested in interaction for altruistic purposes (TONDELLO *et al.*, 2019). These correlations between the user types might complicate the creation of items that only fit one user type, and also, we understand that these correlations between the user types are a theoretical indication that the Hexad is an oblique model.

In the first Confirmatory Factor Analysis, when not correlating the factors, our study did not present a good model fit (χ^2/df = 3.6, RMSEA = 0,125, CFI = 0.702, TLI = 0.673, NFI = 0.673, and SRMR = 0.314), and also two items presented $\lambda \leq 0.5$ (D2: $\lambda = 0.491$, and F2: $\lambda = 0.496$). In our study, similar to Tondello *et al.* (TONDELLO *et al.*, 2019), item F2 presented a low factor loading. Tondello *et al.* (TONDELLO *et al.*, 2019) indicated this item as passive of improvement, suggesting that it would probably fit better with another user type. Considering the problems that other studies presented with the Free Spirit sub-scale, and that the item F2 might be related to other user types (TONDELLO *et al.*, 2019; OOGE *et al.*, 2020), it is important to conduct future studies to improve the sub-scale (specifically the item F2). Regarding item D2, we think a possible problem with the item is the use of the Latin expression “status quo”. In other validation studies, this expression was replaced by another expression in the validation language (TONDELLO *et al.*, 2019; TASKIN; ÇAKMAK, 2020), or the respondents were informed about the meaning of the expression (MANZANO-LEÓN *et al.*, 2020; OOGE *et al.*, 2020). Therefore, we think that a reformulation of this item or a previous explanation about the expression “status quo” to the respondents, could improve the understanding and consequently, the results. In the confirmatory factor analysis correlating the factors, the fit indices were acceptable or close to acceptable (χ^2/df = 2.56, RMSEA = 0.064, SRMR = 0.073, CFI = 0.926, TLI = 0.914, NFI = 0.889, and GFI = 0.882). Overall, the Disruptor sub-scale presented some problems (*i.e.*, items with $\lambda \leq 0.5$, composite reliability below the acceptable, and items presenting modification indices with values that were higher than 30.000), which we understand as an indication that a further investigation about this user type might be necessary to learn more about how people present its characteristics.

Similar to Manzano-León *et al.* (MANZANO-LEÓN *et al.*, 2020), we also conducted Multi-group Confirmatory Factor Analysis to evaluate whether gender could influence the use of the scale. Since we conducted two confirmatory factor analyses, we decided to conduct two Multi-group Confirmatory Factor Analyses (one correlating the factors and another not correlating the factors) to test the invariance of the scale. In both Multi-group Confirmatory

Factor Analyses, the invariance was evaluated using the CFI difference test (ΔCFI ≤ 0.01) indicating unconstrained, metric, and scalar invariance (CHEUNG; RENSVOLD, 2002). Based on our results and the results presented by Manzano-León *et al.* (MANZANO-LEÓN *et al.*, 2020), the Hexad scale is an instrument that can be used regardless of gender.

3.1.4 Limitations and opportunities for future studies

This study has presented some limitations concerning different aspects. Considering the demographic information of the respondents, we were not able to collect answers in all Brazilian states, and also some regions had low participation, which prevented us to present possible correlations between the user types and demographic characteristics. Considering the age of the respondents, most of them were older than 20 years, therefore, the results might not be applicable to children and teenagers. We analyzed the psychometric properties of the Hexad scale translated to Brazilian Portuguese, however, other countries also have Portuguese as the official language (*e.g.* Portugal, Angola, Mozambique), and the instrument used in this study might not be the most suitable to be used in these countries.

Based on these limitations, we identified some studies that could be carried out in the future. *i)* Following other studies that tried to validate the scale for young people (MANZANO-LEÓN *et al.*, 2020; OOGE *et al.*, 2020), future studies can specifically analyze the psychometric properties of the Brazilian Portuguese scale for adolescents. *ii)* Since there were items that did not reach the expected factor loading values in this study, future studies can propose new translations for them as well as new items to measure the Disruptor and Free Spirit sub-scale, improving the reliability in these sub-scales and also the power of these items in the measurement of the Hexad user types. *iii)* Finally, considering that the countries that have Portuguese as the official language present cultural differences and also some differences in the language itself, future studies can adapt the Brazilian Portuguese scale to other Portuguese-speaking countries, making possible the use of the scale in more locations.

3.1.5 Summary

The different analyses conducted in this study demonstrated that the Brazilian Portuguese version of the Hexad scale is an instrument that is near to complete validation and can be used regardless of gender when considering Brazilian adults. Furthermore, the study also indicated that some items should be improved to better identify the user types, which can be a challenge considering the overlaps between the user types. Overall, the scale evaluated in this study can be used to identify the Hexad user types in future research involving Brazilian samples.

3.2 Psychometric investigation of the Hexad scale in Brazilian Portuguese with adolescents

Originally created in English, the Hexad user types scale has been psychometrically investigated in other languages (TONDELLO *et al.*, 2019; AKGÜN; TOPAL, 2018; KRATH; KORFLESCH, 2021). However, less is known about the psychometric investigation of the Hexad scale when considering adolescents, with only two studies focusing on this population. Ooge *et al.* (OOGE *et al.*, 2020), investigated the psychometric properties of Hexad in Dutch and were not able to confirm the validity of the scale, demonstrating that Hexad should not be applied to adolescent Dutch speakers. On the other hand, Manzano-León *et al.* (MANZANO-LEÓN *et al.*, 2020), investigated the psychometric properties of Hexad Spanish and English (with adolescents) and identified suitable results, with no interference observed in regard to gender (*i.e.*, boys and girls comprehended the scale in the same way).

Considering this lack of evaluation of the Hexad scale with adolescents and also that the study presented in section 3.1 considered a sample majority composed of adults, in this study, we present an analysis of the psychometric properties of the Hexad scale in Brazilian Portuguese, considering only adolescents (N=110) aged between 13 and 16 years old.

3.2.1 Method, data collection, and participants

The dataset used in the study was provided by a teacher from a public school in Brazil. The teacher collected the students' age, Hexad user types, and gaming habits following all the indications from the published study of psychometric properties of the Hexad scale in Brazilian Portuguese (SANTOS *et al.*, 2022), using the same scale and also including the same "attention-check" statement. In accordance with the Brazilian National Health Council resolution number 510 published on April 7th, 2016, informed consent for participation was obtained from all participants and their legal guardians, and the final dataset was provided to us without the possibility of identification of the students.

From the 123 responses the dataset provided, 13 were discarded for having missed the attention-check item. Therefore, we analyzed data from 110 participants, with ages ranging from 13 to 16 years old (M = 14.2, SD = 0.68). Most respondents (85%) reported that playing games was a habit, with 45% reporting playing daily, 35% playing rarely, 17% playing weekly, and 5% reporting not knowing how much they play.

3.2.2 Results

To evaluate the properties of the Hexad scale, we analyzed the *i)* descriptive statistics, *ii)* internal reliability, *iii)* correlation between user types, and *iv)* factor analysis of the data. Initially, we analyzed the distribution of the data using the Kolmogorov-Smirnov test, which demonstrated that the scores were not normally distributed. After that, we measured the means and the standard deviations in each Hexad sub-scale, and the internal reliability of the data using Cronbach's α, which results are shown in Table 7. Overall, the reliability scores were acceptable ($\alpha \geq 0.70$), except for the Disruptor and Free Spirit sub-scales. These results are similar to the results from the adult sample (see section 3.1) and to prior studies that analyzed the Hexad scale (TONDELLO *et al.*, 2019; OOGE *et al.*, 2020; TASKIN; ÇAKMAK, 2020; KRATH; KORFLESCH, 2021). Finally, we measured the bivariate correlation coefficients between the user types' scores, which results are shown in Table 7. Since the user type scores were non-parametric, as recommended by Wohlin (WOHLIN *et al.*, 2012), we measured the bivariate correlation coefficients between each Hexad user type using Kendall's τ.

As reported in Table 7, the higher average scores were from the Player and Achiever sub-scales, results that are partially similar to the results from the adult sample (see section 3.1) and to prior studies of the Hexad scale (TONDELLO *et al.*, 2016; TONDELLO *et al.*, 2019; KRATH; KORFLESCH, 2021). The lower average scores were from Disruptors, which is the same result of all the studies that analyzed the Hexad scale (TONDELLO *et al.*, 2019; OOGE *et al.*, 2020; MANZANO-LEÓN *et al.*, 2020; TASKIN; ÇAKMAK, 2020; KRATH; KORFLESCH, 2021; SANTOS *et al.*, 2022). We also calculated the dominant user types (*i.e.*, the strongest tendency (HALLIFAX *et al.*, 2019b)) of each respondent, which distribution results were: Player = 31%, Achiever = 30%, Philanthropist = 16%, Socialiser = 12%, Free Spirit = 8%, and Disruptor = 3%. Most of the respondents (70%) presented more than one dominant user type, with Achiever and Player being the dominant user types of 61% of the respondents (14 students having both dominant user types).

Table 7 – Mean, standard deviation, data variances, internal reliability, and correlations (study 2)

UT	M	SD	α	A	D	F	P	R
A	23.14	5.103	0.750					
D	13.39	4.946	0.527	0.052				
F	21.65	4.042	0.489	0.244**	0.079			
P	21.23	5.154	0.761	0.203**	-0.189**	0.255**		
R	23.12	5.048	0.742	0.323**	0.193**	0.281**	0.162*	
S	20.08	5.567	0.775	0.132	0.039	0.107	0.399**	0.172*

Key: Descriptive analysis, internal reliability, bivariate correlation coefficients (Kendall's τ), and significance between each Hexad user type and all others. N = 110. UT: User type; M: mean score; SD: standard deviation; α: Cronbach's Alpha; A: Achiever; D: Disruptor; F: Free Spirit; P: Philanthropist; R: Player; S: Socialiser. ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

Considering the results of the CFA from the first study with the adult sample (see section 3.1), and also prior studies about the Hexad scale (TASKIN; ÇAKMAK, 2020; AKGÜN; TOPAL, 2018; MANZANO-LEÓN *et al.*, 2020), we conducted the CFA considering the Hexad model as an oblique model (*i.e.*, considering the factors as correlated). In this analysis, the six

Hexad user types were modeled as latent variables correlated with each other, the 24 survey items were modeled as observed variables and the four items associated with each user type were modeled as reflections of the respective latent variable. Figure 3 presents the path model.

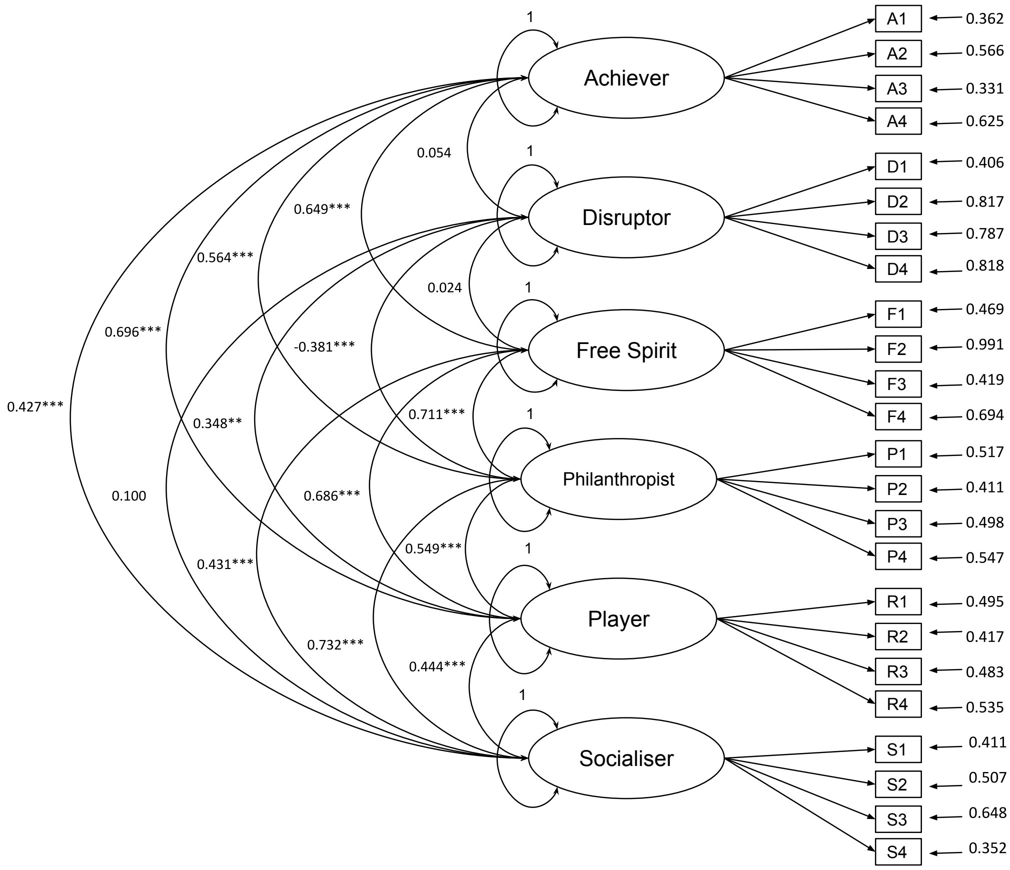


Figure 3 – Path model with correlations between the factors (study 2)

To evaluate the goodness of fit of the model, we initially measured the chi-squared test χ^2 and the RMSEA. The Chi-squared test did not support the evidence for a good model fit (χ^2_{237} = 347.422, $p \leq 0.001$). However, the Chi-squared test is sensitive to the sample size, normally rejecting the model fit when large samples are used and not discriminating good fitting models and poor fitting models when small samples are used (HOOPER; COUGHLAN; MULLEN, 2008). Thus, we calculated the χ^2/df = 1.46, which indicated a good model fit (WHEATON *et al.*, 1977; HOOPER; COUGHLAN; MULLEN, 2008). The RMSEA = 0.065 (CI = [0.050, 0.080]), the CFI = 0.969, the Tucker-Lewis Index (TLI) = 0.964, the NFI = 0.909, and the GFI = 0.960, indicated a well-accepted fitted model (HU; BENTLER, 1999; HAYASHI; BENTLER; YUAN, 2011; HOOPER; COUGHLAN; MULLEN, 2008). However, the SRMR = 0.093 was slightly higher than the indicated as acceptable (HOOPER; COUGHLAN; MULLEN, 2008).

Table 8 present the factor loadings for each of the Hexad survey items. Based on the factor loadings and considering that Cronbach's α may be misleading due to its tendency to underestimate reliability (RAYKOV, 1997), we also measured the composite reliability (CR) of each Hexad sub-scale. The CR is formulated through structural equation modeling and is equivalent to coefficient omega (PADILLA; DIVERS, 2016), being a good option to measure reliability. The results found could be considered acceptable (CR $\geq$ 0.7) for all the factors except the Disruptor and Free Spirit sub-scale (Achiever = 0.816; Disruptor = 0.606; Free Spirit = 0.640; Philanthropist = 0.804; Player = 0.811; and Socialiser = 0.811).

Table 8 – Factor loadings (study 2)

				CI		
UT	**I**	**SE**	**Z-value**	**5%**	**95%**	λ
A	**A1**	0.053	15.048	0.695	0.903	**0.799**
	A2	0.070	9.430	0.522	0.796	**0.659**
	A3	0.057	14.321	0.706	0.930	**0.818**
	A4	0.104	5.868	0.408	0.817	**0.612**
D	**D1**	0.079	9.769	0.616	0.926	**0.771**
	D2	0.098	4.365	0.235	0.619	0.427
	D3	0.083	5.551	0.299	0.625	0.462
	D4	0.093	4.603	0.245	0.609	0.427
F	**F1**	0.065	11.166	0.601	0.857	**0.729**
	F2	0.087	1.080	-0.076	0.264	0.094
	F3	0.064	11.986	0.638	0.887	**0.762**
	F4	0.084	6.607	0.389	0.717	**0.553**
P	**P1**	0.058	12.041	0.582	0.808	**0.695**
	P2	0.052	14.874	0.666	0.869	**0.767**
	P3	0.057	12.410	0.596	0.820	**0.708**
	P4	0.062	10.940	0.552	0.794	**0.673**
R	**R1**	0.055	12.847	0.602	0.819	**0.710**
	R2	0.054	14.162	0.658	0.870	**0.764**
	R3	0.051	14.061	0.619	0.819	**0.719**
	R4	0.073	9.371	0.539	0.825	**0.682**
S	**S1**	0.048	15.978	0.673	0.861	**0.767**
	S2	0.055	12.659	0.593	0.811	**0.702**
	S3	0.065	9.060	0.465	0.721	**0.593**
	S4	0.045	17.959	0.717	0.893	**0.805**

Key: UT: User types/factors; I: Items; SE: standard errors; CR: critical ratios; CI: Confidence interval; λ: standardized λ; bold: $\lambda \geq 0.500$; A: Achiever; D: Disruptor; F: Free Spirit; P: Philanthropist; R: Player; S: Socialiser.

3.2.3 Discussion

Our results indicated significant correlations between the user types, which also corroborate the prior study with the adult sample (see section 3.1). However, while the study with the adult sample indicated significant correlations between all the user types, in this study the significant correlations were presented by 10 of the 15 correlations analyzed. Similar to the study from the adult sample, the strongest correlation happened between Socialisers and Philanthropists (0.399**). Philanthropists and Socialisers have presented a correlation in several studies about the Hexad scale (TONDELLO *et al.*, 2019; TASKIN; ÇAKMAK, 2020; MANZANO-LEÓN *et al.*, 2020; KRATH; KORFLESCH, 2021), which can be explained by the fact that both user types are interested in social interaction. In this study with the adolescent sample, the second strongest correlation happened between Achievers and Players (0.323**). A possible explanation of the correlation between Achievers and Players, which was also found in prior research about the Hexad scale (TONDELLO *et al.*, 2019; TASKIN; ÇAKMAK, 2020; MANZANO-LEÓN *et al.*, 2020; KRATH; KORFLESCH, 2021), can be the fact that both users types are motivated by achievement.

In the CFA, we followed the studies conducted by Akgün and Topal (AKGÜN; TOPAL, 2018), Taşkın and Çakmak (TASKIN; ÇAKMAK, 2020), Manzano-León *et al.* (MANZANO-LEÓN *et al.*, 2020), and Santos *et al.* (SANTOS *et al.*, 2022) (*i.e.*, our previous study), that indicated the factors should be modeled as correlated in the analysis. Overall, our study presented a good fit model (χ^2/df = 1.46, RMSEA = 0.065, CFI = 0.969, TLI = 0.964, NFI = 0.909, GFI = 0.960, and SRMR = 0.093), however, the factor loadings of the Disruptor (items 1, 2, and 3) and Free Spirit (item 2) sub-scales indicated problems with items ($\lambda \leq 0.5$). These items were the same items that presented $\lambda \leq 0.5$ in the study with the adult sample (see section 3.1). We understand that this is an indication that the translation of items D1, D2, D3, and F4 into Brazilian Portuguese is not effective and should be reviewed. The worst λ value presented in this study was from item F2. When considering the analyses that were made considering the Hexad as an oblique model (*i.e.*, modeling the analysis without correlation between the factors), the study conducted by Ooge *et al.* (OOGE *et al.*, 2020) with adolescents also indicated problems with the Free Spirit sub-scale. However, this might not be correlated with the age of the respondents, since the study of Tondello *et al.* (TONDELLO *et al.*, 2019) indicated that item F2 presented a low factor loading, and suggested that this item would probably fit better with another user type.

Regarding the problems presented by the Disruptor sub-scale, the lowest λ values were from D2 and D4. As reported in the study with the adult sample, we understand that a possible explanation for the results of item D2 was the use of the Latin expression "status quo". The other two studies that have analyzed the psychometric properties of the scale with an adolescent sample (MANZANO-LEÓN *et al.*, 2020; OOGE *et al.*, 2020), have explained to the respondents its meaning before the survey application, and other studies have replaced the expression with another expression in the validation language (TONDELLO *et al.*, 2019; TASKIN; ÇAKMAK, 2020). We understand that there is a necessity for this item reformulation to improve the measurement of this user type. However, considering that most of the items of the Disruptor sub-scale have presented a low factor loading in this study, the current Brazilian version of the Disruptor sub-scale might not be suitable to evaluate this user type from adolescents.

3.2.4 Limitations and opportunities for future studies

Our study has some limitations considering the following aspects: *i)* sample size and *ii)* age of participants. Regarding the sample size, we used a provided sample that was collected in one school in Brazil, which prevented us to analyze a bigger sample or indicating possible correlations between the user types and demographic characteristics. Also, all the participants were from 13-16 years, therefore, the scale might not be applicable to people younger than 13 years old. Considering that the sample analyzed in our prior study of the Brazilian Portuguese version of the Hexad scale was majority composed of people older than 20 years, there is no evidence that the scale can measure well the user types from people aged between 17 and 20 years.

These limitations create some possibilities that can be carried out in the future. Even though the Brazilian Portuguese version of the Hexad scale has been analyzed in two studies with two different samples, the scale has not been yet analyzed with children. Future studies can tackle this challenge, and which results could be very useful to designers and researchers in the development of gamified settings for them. In this study, the items D2, D3, D4, and F2 did not reach the expected factor loading values. Also, the same items have presented problems in the prior study with a Brazilian adult sample. We believe future studies should propose new translations for these items or new items to measure the Disruptor and Free Spirit sub-scales. These improvements seemed to be necessary for better measurement of the Hexad user types.

3.2.5 Summary

In this study, we analyzed the psychometric properties of the Hexad scale in Brazilian Portuguese considering an adolescent sample. Our results indicated that five of the six Hexad user types can be well evaluated with the current version and indicated the items that need improvement. This study also indicated overlaps between the user types. Having an appropriate scale to measure the Hexad user types of adolescents can help designers and the industry in the creation and personalization of several types of gamified systems for this population.

3.3 Chapter Conclusion

This chapter presented two studies that were conducted to evaluate the Brazilian Portuguese version of the Hexad scale. Even though the Hexad scale was analyzed in different languages since its development, our studies were the first to analyze it in Brazilian Portuguese. Our results indicated that the current translated version can be used to properly evaluate most of the Hexad user types from adolescents and adults. Moreover, the results also indicated that the scale can be used for adults regardless of gender. In addition, both studies indicated items should be reviewed (especially the items from the Disruptor sub-scale), in order to improve the identification of the Hexad profiles in Brazilian samples. Besides the indication that the scale in Brazilian Portuguese was properly measuring the profiles of the participants in this research, these studies allowed other studies to use it to identify the Hexad user types in future research involving Brazilian samples.

CHAPTER

4

HOW DO THE USER TYPES CHANGE OVER TIME AND HOW TO MODEL USER PROFILES BASED ON THESE CHANGES?

This chapter presents the studies conducted with the goal of analyzing whether the user types change and how to model user profiles based on these changes. Initially, we conducted an exploratory study to analyze whether the user types change after six months of the first profile evaluation. This study (see Appendix A) was published as a full paper at the 5th International GamiFIN Conference (SANTOS *et al.*, 2021a). After that, we conducted a further analysis of the changes as well as indicated possible patterns of change and how to model user profiles based on that. This second study is under review at the Annual Symposium on Computer-Human Interaction in Play (CHI PLAY).

4.1 Exploratory analysis on how user types change over time

Despite the growing number of researches about the personalization of gamified environments (KLOCK *et al.*, 2020; STUART; LAVOUÉ; SERNA, 2020), the results are still contradictory, and not always, the user models are faithful to each person's preferences, as well as, not always, personalization has positive effects on the users experience (KLOCK *et al.*, 2020). Some recent studies argue that one of the reasons for the contradictory results in research about the personalization of gamified environments is that users' preferences may change over time (BUSCH *et al.*, 2016; KLOCK *et al.*, 2020), and thus, user models would need to be dynamic, as well as the personalization of gamified systems. However, in general, studies on this field are theoretical and few empirical studies have been carried out until today (KLOCK *et al.*, 2020; BUSCH *et al.*, 2016), not allowing to know if the user types change over time in the gamification context.

Facing this challenge, in this study, we conducted an exploratory analysis with data from 74 participants to identify if the Hexad user types would change over time. We focused on answering the question “Do people’s user types (Achiever, Philanthropist, Socialiser, Free Spirit, Player, and Disruptor) change over time (six months)?”. The results obtained have theoretical and practical implications in the design of gamified environments, indicating that the user types of participants possibly change over time. Therefore it is not enough to analyze the participant’s user types once, as well as that the static personalization of the gamification might not be enough to provide a good experience for users, being necessary to invest in approaches to provide dynamic personalization, *i.e.*, that changes according to the changing profile of users.

4.1.1 Method, data collection, and participants

The study was divided into two phases, with the same survey being applied through Google Forms. The survey consisted of 32 questions divided into two different sections, the first section being used to collect the participants’ demographic information (age, gender (options were: male, female, other, and I prefer to not inform), educational level, state (options were the 26 Brazilian states and the Federal District)) and gaming habits (if the respondent play games and the frequency (options were: every day, every week, rarely, and I do not know)), and the second section being used to collect the Hexad user type of the participants. To collect the Hexad user type of the participants, we used the Brazilian version of the scale, which results of its psychometric properties were presented in section 3.1. The Hexad scale items were randomly presented on a 7-point Likert scale (LIKERT, 1932), and we also included an “attention-check” statement in the middle of the second section, to check if people were paying due attention when reading and answering the form. Responses from people who missed the attention-check statement were removed from the data analysis. After the development of the survey in the first phase of the study, as recommended by Connelly (CONNELLY, 2008), we conducted a pilot study. Our pilot study was conducted with ten respondents, that analyzed if the size of the survey was appropriate. Eight respondents answered that the survey was not too long, then any question was taken away from it.

For the first phase, the survey was spread on social networks (Facebook, Twitter, and Instagram) and e-mail (public lists from universities). Were collected 366 answers, of which 331 were valid according to the attention-check item. In this phase of the study, the participants could leave their e-mails for future studies, however, this question was not obligatory. From these 331 answers, 182 respondents provided a valid e-mail and authorized the contact for other studies. These 182 e-mails were provided by 90 people that self-reported as women (49%) and 92 people that self-reported as men (51%). 71% of the respondents reported that playing games was a habit. 56% of the respondents presented only one of the six Hexad’s user types (Achiever, Philanthropist, Socialiser, Disruptor, Free Spirit, and Player) as the dominant user type, while the other 44% presented twenty-two different combinations of the six Hexad's user types as dominant user type (*e.g.*, Achiever and Philanthropist, Philanthropist and Socialiser).

After six months of this data collection, the survey of the second phase was sent to all the 182 respondents that left a valid e-mail in the first phase. Were collected 87 answers, of which 74 were valid according to the attention-check item. In this phase, 57% of the respondents presented only one of the six Hexad's user types (Achiever, Philanthropist, Socialiser, Disruptor, Free Spirit, and Player) as the dominant user type, while the other 43% presented twenty-two different combinations of the six Hexad's user types as dominant user type (*e.g.*, Achiever and Philanthropist, Philanthropist and Socialiser). Table 9 presents the demographic information and gaming habits of the respondents that participated in both phases of the study.

Table 9 – Demographic information and gaming habits of the participants of both phases (SANTOS *et al.*, 2021a)

Demographic information					
Gender	Female	55%	Age	15-19	5%
	Male	45%		20-24	12%
Education level				25-29	16%
	Basic Education	4%		30-34	14%
	Bachelor	27%		35-39	14%
	Specialized courses	27%		40-44	18%
	M.Sc.	26%		45-49	11%
	PhD	9%		50-54	5%
	PostDoc	7%		55-59	4%
				Over 60	1%
Gaming habits					
Play games		72%	Do not play games		28%
Frequency	Everyday	14%			
	Every week	16%			
	Rarely	54%			
	I do not know	16%			

To evaluate the dominant user type of the participants in both phases, we measured all the scores that each participant presented in each sub-scale (*i.e.*, the four items of each Hexad user type) and calculated where they presented the higher average score. Instead of grouping the respondents only in the six Hexad user types, the respondents that presented the higher average score repeated in more than one sub-scale were grouped into the combination (*e.g.*, if the respondent presented as repeated score 28 in the Achiever and Player sub-scale, his/her dominant user type is the Achiever and Player).

Participation in the pilot study and both research phases was voluntary, thus, was not offered to the respondents any remuneration or gifts. Since the size of the survey and the quality of the answers were a concern before the data collection, we understand that, as volunteers, respondents are more willing to pay attention when answering the survey. Tondello and Nacke

(TONDELLO; NACKE, 2020) also presume that volunteers participate in studies without pressure to maximize time usage, which can provide more quality answers.

4.1.2 Results

Initially, we measured the internal reliability for each Hexad user type in both phases of the research. Overall, the reliability was acceptable ($\alpha \geq 0.70$, RHO A ≥ 0.70, CR ≥ 0.70, AVE ≥ 0.50) for all user types, except for the user type Disruptor (in both phases) and Free Spirit (first phase), which were slightly below the acceptable. Cronbach's α values under 0.7 for the Disruptor and Free Spirit scales were also found in other recent studies (TONDELLO *et al.*, 2019; OOGE *et al.*, 2020). The reliability results can be seen in Table 10.

Table 10 – Reliability results (SANTOS *et al.*, 2021a)

Construct	α	**RHO**	**CR**	**AVE**
Achiever1	**0.863**	**0.924**	**0.874**	**0.642**
Achiever2	**0.845**	**1.148**	**0.883**	**0.655**
Disruptor1	0.648	0.668	**0.790**	0.486
Disruptor2	0.660	0.691	**0.794**	0.494
Free Spirit1	0.676	**0.987**	**0.758**	0.451
Free Spirit2	**0.785**	**0.813**	**0.853**	**0.593**
Philanthropist1	**0.873**	**0.987**	**0.909**	**0.716**
Philanthropist2	**0.890**	**0.914**	**0.924**	**0.754**
Player1	**0.743**	**0.813**	**0.830**	**0.552**
Player2	**0.851**	**0.855**	**0.900**	**0.694**
Socialiser1	**0.862**	**0.987**	**0.903**	**0.702**
Socialiser2	**0.883**	**0.893**	**0.919**	**0.740**

Key: α: Cronbach's; RHO: Jöreskog's rho; CR: Composite Reliability; AVE: Average Variance Extracted; 1: results of the first research phase; 2: results of the second research phase; Values in grey are $\alpha < 0.70$, RHO A < 0.70, CR < 0.70, AVE < 0.50

Analyzing the dominant user types it was possible to discover that 57 people (76% of the participants) presented a change in the dominant user type after six months. The 74 participants presented in the first phase of the study, 19 different user types combinations as the dominant user type, with 51% presenting a combination of more than one user type as the strongest tendency. In the second phase, the 74 participants presented 20 different user types with 43% presenting a combination of more than one user type. Women (78%) changed the strongest tendency more than men (73%), as well as people who play (77%) changed more than people who do not play (71%). People with a master's degree (32%) were those who more changed the dominant user type in the educational level group. Considering only the age, six of the ten age groups measured in this research, presented a change of more than 75% (15-19 years - 100%; 20-24 years - 89%;

25-29 years - 92%; 30-34 years - 80%; 40-44 years - 92%; 50-54 years - 75%). Table 11 presents the different combinations that the 74 respondents presented as dominant user types in both phases of the study.

Table 11 – Dominant user type of participants (SANTOS *et al.*, 2021a)

User type	**1st**	**2nd**
Philanthropist	24%	23%
Achiever	12%	16%
Free Spirit	5%	8%
Socialiser	3%	3%
Disruptor	3%	3%
Player	1%	4%
Achiever/Philanthropist	20%	8%
Achiever/Free Spirit/Philanthropist/Player/Socialiser	4%	-
Achiever/Free Spirit/Philanthropist	4%	4%
Free Spirit/Player	4%	3%
Philanthropist/Player	4%	3%
Achiever/Player	3%	1%
Achiever/Philanthropist/Player/Socialiser	3%	3%
Achiever/Socialiser	3%	3%
Achiever/Philanthropist/Socialiser	1%	1%
Philanthropist/Socialiser	1%	5%
Achiever/Free Spirit/Philanthropist/Player	1%	3%
Achiever/Free Spirit	1%	5%
Free Spirit/Philanthropist/Player/Socialiser	1%	-
Achiever/Player/Socialiser	-	1%
Free Spirit/Philanthropist/Socialiser	-	1%
Player/Socialiser	-	1%
Key: 1st: First research phase; 2nd: Second research phase.		

Then, we calculated the average score for each user type in the research. Since each Hexad sub-scale is formed by four items arranged in a 7-point Likert Scale, the maximum value a Hexad sub-scale can be is 28. Similar to other studies that accessed the user type through the Hexad scale (TONDELLO *et al.*, 2016; TONDELLO *et al.*, 2019; ALTMEYER *et al.*, 2020b), the Philanthropists and Achievers presented the higher average score while the Disruptors presented the lower average score. After testing the normality of the data using the Shapiro-Wilk test, we measured the bivariate correlation coefficients using Kendall's τ, since the user type scores were non-parametric. Considering the conversion table proposed by Gilpin (GILPIN, 1993), the Achievers' scores between the research phases presented a weak correlation while Socialisers', Free Spirits', Philanthropists', Disruptors', and Players' scores presented a moderate correlation. Table 12 reports the average scores, the standard deviation, and the bivariate correlation coefficients (Kendall's τ). These results indicate that, besides the differences in the dominant user types, the six Hexad sub-scales also presented differences in the average scores in both phases.

Table 12 – Mean scores, standard deviation, and bivariate correlation coefficients (Kendall's τ) (SANTOS *et al.*, 2021a)

User Types	Mean score	S.D.	τ
Achiever1	24,69	4,03	20,265**
Achiever2	23,39	4,72	
Disruptor1	15,72	5,27	0,434**
Disruptor2	15,07	5,33	
Free Spirit1	23,42	3,98	0,365**
Free Spirit2	22,43	4,83	
Philanthropist1	24,92	4,07	0,379**
Philanthropist2	24,22	4,43	
Player1	21,18	4,99	0,478**
Player2	21,03	5,59	
Socialiser1	20,88	5,44	0,358**
Socialiser2	21,16	5,44	

Key: τ: Kendall's tau; 1: results of the first research phase; 2: results of the second research phase; ** p<0.01; P: Philanthropist; A: Achiever; R: Player; F: Free Spirit; S: Socialiser; D: Disruptor.

4.1.3 Discussion

This study examined if Hexad's user types of 74 participants presented differences after six months of the first evaluation. We analyzed the differences among the dominant user types and also the differences presented in the scores of the six Hexad sub-scales. Overall, our findings indicated that most of the participants presented changes in their dominant user types, and also the six Hexad sub-scales presented differences in the average scores after six months.

When we consider only the dominant user type (*i.e.*, the strongest tendency), 76% of the participants presented a change in the score. As showed in Table 11, some dominant user types have presented a considerable change between the research phases (*e.g.*, Achiever/Philanthropists were 20% of the participants of the first research phase and decreased to 8% in the second). Also is notable that in both phases, all the participants of some dominant user types have changed (*e.g.*, Achiever/Player/Socialiser did not appear in the first research phase; Free Spirit/Philanthropist/Player/Socialiser appeared only in the first research phase). These results can be related to the results found by Busch *et al.* (BUSCH *et al.*, 2016), which indicated that, in the game context, some player types can be less stable over time. Our results indicate that users present changes in the dominant user type (*i.e.*, the strongest tendency) over time, and consequently, the dominant user types can not be considered stable.

Our results also indicate that even when we consider only the dominant user type, users can present more than one of the basic Hexad user types (*i.e.*, Achiever, Philanthropist, Socialiser, Free Spirit, Player, and Disruptor) as the dominant user type. As can be seen in Table 11, in the first research phase there were more participants disposed in more than one user type (*i.e.*, Achiever/Philanthropist = 20%) than participants disposed in some of the basic Hexad user types (*i.e.*, Achiever = 12%, Free Spirit = 5%, Socialiser = 3%, Disruptor = 3%, and Player = 1%). As indicated by previous studies (TONDELLO *et al.*, 2016; TONDELLO *et al.*, 2019), some user types seem to be correlated, which might explain why some respondents presented more than one user type as the dominant user type. Since the user performance can be affected by the user type (LOPEZ; TUCKER, 2019), we believe that, when considering only the dominant user type, it is necessary to analyze if the user presents more than one user type as the dominant.

Considering the demographic information of the respondents that changed the dominant user type, women seem to be slightly more susceptible to changing the dominant user type than men. The study conducted by Tondello *et al.* (TONDELLO *et al.*, 2019) showed that women scored higher in the intrinsically motivated user types (*i.e.*, Achiever, Philanthropist, Socialiser, and Free Spirit), and since our results showed that the user types Achiever, Philanthropist, and Free Spirit presented the higher difference in the average scores of both research phases, we believe that women might be more susceptible to change the user type than men because they are more motivated by the intrinsically motivated user types. From the descriptive analysis, it was not possible to identify how age can influence the user types' change, since the changes varied in the age groups measured in this study. Despite that, our results demonstrate that people can change their user types in different life stages, showing that to personalize gamification it is important to consider other characteristics besides the user type and age group of the users.

Even though the results about the differences presented between the user types in both research phases (see Table 12) can be considered small (all the user types presented less than 1.3 points of difference in the average scores, from 28 available), we understand that when we consider all the average scores of the user types, the participants' changes might have produced an offsetting change. Thus, some participants might have increased a particular item while some decreased in the same item, therefore, producing offsetting changes.

4.1.4 Limitations and opportunities for future studies

Our study has some limitations inherent to the type of study, which we sought to mitigate. Initially, the limited number of participants, as well as the fact that the participants were from the same country (*i.e.*, Brazil) can prevent the generalization of the results. To mitigate this limitation we used static methods to guarantee the reliability of the data. To access all the necessary information about the respondents we used a survey that might be considered long (32 questions and items) for the respondents, thus, to mitigate this limitation, we conducted a pilot study asking the participants if they considered the size of the survey adequate for the research. It is possible that some participants might have not paid attention when answering the survey and to mitigate this limitation, all the respondents were volunteers and we inserted an "attention check item", eliminating responses from participants who missed this question.

Considering the obtained results and the limitations of this study, it is possible to define some studies that can be conducted in the future. This study was conducted without considering a specific domain, and the gamification effects can vary according to the context (HALLIFAX *et al.*, 2019b). Thus, future studies can replicate this study in specific contexts (*e.g.*, health, education, business) to analyze how the context affects the user type changes, furthering our results.

Similar to other studies about player/user types (BUSCH *et al.*, 2016; TONDELLO *et al.*, 2019), we were able to evaluate the user types of the respondents at different moments, and it was possible to identify that the number of participants tends to decrease when the research is conducted in more than one phase. One possible reason for the reduction of participants in our research is there was not any kind of intervention with the respondents between the study phases. Considering that the number of participants can reduce the exploratory power of the results (KOIVISTO; HAMARI, 2019), and prevent the generalization of the results, we recommend that future studies should be conducted with a larger sample and with interventions between the phases. Similar to Busch *et al.* (BUSCH *et al.*, 2016), we waited six months to analyze if the respondents presented any difference in their user types. It is important to analyze if the participants can present changes in their user type earlier (*e.g.*, after two or three months), as well as if the respondents can return to the first user type after a longer period (*e.g.*, after a year). We suggest that future studies on this topic should have more phases (*e.g.*, two months, a year), considering the evaluation of the user types stability in a shorter and longer period.

Our study identified there were differences between most of the respondents' user types after six months, confirming the hypothesis that the profile of people changes and directly influences the style of personalization that should be carried out (*i.e.*, demonstrating the importance of dynamic personalization). Although recent studies (ALTMEYER *et al.*, 2019b; ALTMEYER *et al.*, 2020b) showed that the prediction of the Hexad user types might be a possibility, the user type is still mostly accessed through surveys and questionnaires (KLOCK *et al.*, 2020). Considering that our results imply having to constantly analyze the user's type, making the process more costly by making users need to answer the survey constantly, future studies should be done to try to predict people's user type based on interaction data, machine learning, or based on the survey response the first time (*i.e.*, predict what the user will be after a certain time, based on survey responses only once).

4.1.5 Summary

As outlined, the user types can not be considered stable after six months. Most of the participants presented different dominant user types and also the results showed differences in the average scores of the user types in both phases. Our results demonstrated that when designing gamified environments based on user types it is necessary to measure the users' scores after a certain period. The personalization of gamified environments also needs to follow the user changes, guaranteeing that the personalization supports the user constantly.

4.2 Modeling profiles based on the user types changes over time

Regarding the player and user typologies, the most researched user's characteristic in the gamification field (KLOCK *et al.*, 2020; OLIVEIRA *et al.*, 2022b), some studies have indicated that the user models were dynamic (BARTLE, 1996; BUSCH *et al.*, 2016; YILDIRIM; ÖZDENER, 2021), *i.e.*, changes in the user profile happen after a certain time and affect the user experience in a personalized gamified system. However, these studies were theoretical (BARTLE, 1996), only considered player typologies created for games (BARTLE, 1996; BUSCH *et al.*, 2016), or only conducted exploratory analysis about the user types changes (YILDIRIM; ÖZDENER, 2021). Therefore, even though prior research has indicated that user profiles are not stable over time and consequently these changes in the user profile implicate a necessity of dynamic modeling of gamified settings, little is known about these changes and how is possible to model user profiles based on them.

To face the challenge of better understanding how the user profiles change over time, we conducted this study in two different phases measuring the rank-order consistency of the Hexad user types (*i.e.*, Achiever, Philanthropist, Socialiser, Free Spirit, Player, and Disruptor) of 118 participants after six months. The main goal was to answer the following questions: **Which is the relationship between the gamification user types in the first and second data collection (after six months)?** and **How to model user profiles based on this relationship?** Our results indicate that *i)* some user types are more stable over time than others and *ii)* the demographic aspects of the user can influence the changes (*e.g.*, people who have gaming habits present slightly more stable user types than people who do not have gaming habits). These results provide new insights for gamification researchers and practitioners on how to create more effective gamified systems, by indicating some patterns of change and how to model user profiles based on them.

4.2.1 Method, data collection and participants

To evaluate how the user types change over time, we used the same dataset collected in section 4.1, and the dataset that was provided in the section 3.2. The dataset provided in the section 3.2, had 53 answers from students who answered the Hexad scale in two different moments. Three answers from the first phase and six answers from the second phase were removed after checking the "attention-check" item, therefore, the final dataset was formed by 44 respondents. Regarding this specific dataset that was aggregated to our original data, in the first phase of the study 36% of the students presented Player as their dominant user type; 34% presented Achiever as their dominant user type; 11% presented Philanthropist as their dominant user type; 9% presented Socialiser as their dominant user type; 8% presented Free Spirit as their dominant user type; and 2% presented Disruptor as their dominant user type. In this phase, 89%

of the adolescents reported that playing games was a habit. In the second phase of the collection of data from the adolescents, 28% of them presented Player as their dominant user type, 27% presented Achiever as their dominant user type, 18% presented Philanthropist as their dominant user type, 13% presented Socialiser as their dominant user type, 8% presented Free Spirit as their dominant user type, and 5% presented Disruptor as their dominant user type. In this phase, 82% of the adolescents reported that playing games was a habit.

Considering prior studies that used the Hexad scale and merged different datasets (KRATH *et al.*, 2023), the literature suggestion of a minimum sample of 100 participants for studies of this nature (LOEHLIN, 1998), that both datasets were measuring the changes in the user types after six months using the same scale, and that most of the demographic information collected from the respondents were the same, we merged the datasets to conduct one unique analysis. The only information excluded before the analysis was the gender of the participants, considering that this information was not provided in the second dataset. Table 13 presents the demographic information and gaming habits of the respondents from both datasets (first phase N = 226; second phase N =118).

Table 13 – Demographic information and gaming habits of the participants from both phases (study 4)

Demographic information							
		1st phase	2nd phase			1st phase	2nd phase
					13-15	19%	23%
					15-19	8%	18%
Gender*	Female	49%	55%		20-24	9%	8%
	Male	51%	45%		25-29	13%	11%
				Age	30-34	14%	8%
	Elementary/Middle/High School	27%	40%		35-39	9%	8%
	Bachelor	19%	17%		40-44	11%	12%
Education level	MBA/Specialists	20%	14%		45-49	8%	6%
	M.Sc.	24%	19%		50-54	5%	3%
	PhD/PostDoc	10%	10%		55-59	3%	3%
					Over 60	1%	1%
Gaming habits							
		1st phase	2nd phase			1st phase	2nd phase
	Play games	75%	77%	Do not play games		25%	23%
	Everyday	22%	20%				
Frequency	Every week	21%	26%				
	Rarely	41%	42%				
	I do not know	16%	12%				

Key: Gender*: considering that the database from the students did not provide gender, this information is only from the data collected in the study presented in section 4.1.

4.2.2 Results

Initially, we conducted a Shapiro-Wilk test to assess whether the data was following a parametric or non-parametric distribution. Then, we analyzed the *i)* descriptive statistics (mean and the standard deviation in each sub-scale), *ii)* internal reliability (using Cronbach's α and Composite Reliability), and *iii)* correlation between user types (using Kendall's τ). To conduct further analysis of the relationship between the data from both phases of the study and therefore be able to indicate how to model the user profiles, we used Partial Least Squares Path Modeling

(PLS-PM), a reliable method for estimating cause-effect relationship models with latent variables (HAIR *et al.*, 2016).

Overall, the reliability was acceptable ($\alpha \geq 0.70$, CR ≥ 0.70, AVE ≥ 0.50) for all user types, except for the user type Disruptor (in both phases) and Free Spirit (in the first phase). We also measured the discriminant validity finding acceptable values for most of the variables (exception occurred between F1 and A1; F2 and A2; and D1 and D2), since the square root of the variables' AVE value was larger than the correlations the variable had with the other variables, and of the variables presented correlations between them below 0.85. The reliability results can be seen in Table 14 and the discriminant validity can be seen in Table 15.

Table 14 – Reliability results (study 4)

Construct	α	**RHO**	**CR**	**AVE**
Achiever1	0.816	0.988	0.857	0.603
Achiever2	0.803	0.827	0.866	0.619
Disruptor1	0.644	0.657	0.789	0.486
Disruptor2	0.613	0.619	0.775	0.464
Free Spirit1	0.577	0.641	0.703	0.394
Free Spirit2	0.725	0.729	0.826	0.545
Philanthropist1	0.840	0.846	0.893	0.678
Philanthropist2	0.842	0.868	0.892	0.674
Player1	0.766	0.790	0.848	0.582
Player2	0.812	0.820	0.876	0.639
Socialiser1	0.831	0.844	0.888	0.665
Socialiser2	0.846	0.847	0.897	0.685

Key: α: Cronbach's; RHO: Jöreskog's rho; CR: Composite Reliability; AVE: Average Variance Extracted; 1: results of the first research phase; 2: results of the second research phase; Values in grey are $\alpha \leq 0.70$, RHO ≤ 0.70, CR ≤ 0.70, AVE ≤ 0.50.

After measuring the reliability of the data, we calculated the dominant user types (*i.e.*, the strongest tendency of the participants) in both phases of the study, considering the highest score the participant had on the Hexad scale. Since some respondents presented a repeated score as the highest score in different sub-scales, different combinations beyond the six main Hexad user types were presented. Overall, twenty-eight different combinations between the Hexad scale were presented as dominant user types of the respondents, with some combinations appearing only in one phase of the study, which demonstrated that the participants of the study presented changes between the phases. All the combinations can be seen in Table 16. When comparing the dominant user types of the participants in both phases (N=118), 85 participants (72%) presented changes. Therefore, most of the participants changed their dominant user type after six months.

After calculating the dominant user types, we calculated the average score, the standard deviation, and the bivariate correlation coefficients (Kendall's τ) for each sub-scale, which results

Table 15 – Discriminant Validity (study 4)

	A1	A2	D1	D2	F1	F2	P2	P1	R1	R2	S1
A2	0.253										
D1	0.338	0.203									
D2	0.161	0.376	0.865								
F1	0.889	0.288	0.637	0.357							
F2	0.225	0.873	0.347	0.517	0.453						
P2	0.073	0.715	0.095	0.295	0.236	0.770					
P1	0.718	0.148	0.274	0.233	0.748	0.156	0.377				
R1	0.729	0.299	0.390	0.231	0.671	0.276	0.134	0.431			
R2	0.161	0.750	0.183	0.335	0.184	0.758	0.516	0.164	0.538		
S1	0.534	0.198	0.270	0.195	0.541	0.247	0.308	0.724	0.469	0.165	
S2	0.150	0.487	0.145	0.257	0.205	0.448	0.715	0.251	0.110	0.411	0.441

Key: P1: Philanthropist first research phase; A1: Achiever first research phase; R1: Player first research phase; F1: Free Spirit first research phase; S1: Socialiser first research phase; D1: Disruptor first research phase; P2: Philanthropist second research phase; A2: Achiever second research phase; R2: Player second research phase; F2: Free Spirit second research phase; S2: Socialiser second research phase; D2: Disruptor second research phase. Values in grey (F1 and A1; F2 and A2; and D1 and D2) did not present acceptable values.

can be seen in Table 17. Each Hexad sub-scale is formed by four items arranged in a 7-point Likert Scale, therefore, the minimum value a Hexad sub-scale can be is 4 and the maximum is 28. Similar to prior research (TONDELLO *et al.*, 2016; TONDELLO *et al.*, 2019; ALTMEYER *et al.*, 2020b), in both phases of the study the participants presented the higher average score in the Philanthropist and Achiever sub-scale, while presented the lowest average score in the Disruptors sub-scale. After the Shapiro-Wilk test result indicated that the data followed a non-normal distribution, we measured the bivariate correlation coefficients using Kendall's τ, since the data were non-parametric. Considering the conversion table proposed by Gilpin (GILPIN, 1993), the scores of Achievers, Free Spirits, and Socialisers presented a weak correlation, while the scores from Philanthropists, Disruptors, and Players presented a moderate correlation. Therefore, besides the differences in the dominant user types presented in Table 16, the six Hexad sub-scales also presented differences in the average scores between both phases.

We also measured the differences in the dominant user types based on the demographic and gaming habits that the respondents reported in the second phase of the research by calculating how much of each group changed after six months. Based on the age of the participants, the results indicated that most of the age groups presented changes in the dominant user types, which can indicate that changes happen during all life stages. Similar results were found when considering the different educational levels presented by the participants of this study. When considering only the gaming habits, 70% of the participants that expressed that gaming was a habit changed their dominant user type after six months against 78% of the participants that answered that they did not play games. This might indicate that people who have gaming habits could present more stable user types after six months. The percentage of change of each

Table 16 – Dominant user type (study 4)

User type	1st	2nd
Philanthropist	19%	20%
Achiever	17%	17%
Player	11%	8%
Free Spirit	7%	8%
Socialiser	3%	5%
Disruptor	3%	3%
Achiever/Free Spirit	1%	3%
Achiever/Free Spirit/Philanthropist	2%	3%
Achiever/Free Spirit/Philanthropist/Player	1%	-
Achiever/Free Spirit/Philanthropist/Player/Socialiser	3%	2%
Achiever/Free Spirit/Player	3%	-
Achiever/Philanthropist	14%	6%
Achiever/Philanthropist/Player/Socialiser	3%	2%
Achiever/Philanthropist/Socialiser	2%	1%
Achiever/Player	6%	4%
Achiever/Player/Socialiser	1%	1%
Achiever/Socialiser	2%	2%
Free Spirit/Philanthropist/Player/Socialiser	1%	1
Free Spirit/Player	1%	1%
Philanthropist/Player	3%	3%
Philanthropist/Player/Socialiser	1%	-
Philanthropist/Socialiser	1%	3%
Achiever/Free Spirit/Player/Socialiser	-	1%
Free Spirit/Philanthropist/Socialiser	-	1%
Player/Socialiser	-	3%
Achiever/Disruptor/Free Spirit	-	1%
Achiever/Philanthropist/Player	-	1%
Free Spirit/Philanthropist	-	1%

Key: 1st: First research phase; 2nd: Second research phase.

demographic group is presented in Table 18.

Finally, to further calculate how well the answers of the first and second phases of the research were associated, and how we could model the user types based on their changes, we used the Partial Least Squares Path Modeling (PLS-PM), a method of structural equation modeling that has been used in recent studies about gamification (ORJI; TONDELLO; NACKE, 2018; HALLIFAX *et al.*, 2019b; HALLIFAX; LAVOUÉ; SERNA, 2020). The PLS-PM is a reliable method for estimating cause-effect relationship models with latent variable (HAIR *et al.*, 2016) which permits the evaluation of associations between variables (HALLIFAX; LAVOUÉ; SERNA, 2020) and can produce estimates even in small samples (BENITEZ *et al.*, 2020). In this analysis, we calculated the association between each of the Hexad user types scores from the first phase of the study with the user type itself and the other five Hexad user types scores from the second phase of the study. To do this, we considered all the scores presented by the participants, which

Table 17 – Mean scores, standard deviation, and bivariate correlation coefficients (Kendall's τ) - (study 4)

User Types	**Mean score**	**S.D.**	Δ	τ
Achiever	24.24	4.34	0.95	0.301**
Achiever2	23.29	4.87		
Disruptor1	14.62	5.35	-0.18	0.376**
Disruptor2	14.80	5.18		
Free Spirit1	22.83	3.80	0.77	0.280**
Free Spirit2	22.06	4.65		
Philanthropist1	23.25	4.94	0.10	0.418**
Philanthropist2	23.15	4.75		
Player1	22.10	5.16	0.40	0.442**
Player2	21.70	45.38		
Socialiser1	20.50	5.50	-0.18	0.347**
Socialiser2	20.68	5.58		

Key: τ: Kendall's tau; 1: results of the first research phase; 2: results of the second research phase; ** p<0.01; Δ: difference between the phases.

Table 18 – Changes in the dominant user types considering demographic and gaming habits information (study 4)

		% of change			% of change
Educational Level	Elementary/Middle/High School	68%	*Age*	13-14	67%
	Bachelor	75%		15-19	71%
	MBA/Specialists	75%		20-24	80%
	M.Sc.	74%		25-29	77%
	PhD/PostDoc	75%		30-34	80%
Gaming Habits	Play games	70%		35-39	56%
	Do not play games	78%		40-44	93%
Frequency	Everyday	79%		45-49	57%
	Every week	58%		50-54	100%
	Rarely	78%		55-59	33%
	I don't Know	71%		Over 60	0%

means that all participants' tendencies scores were considered and not only the dominant user type. This analysis has as its main objective to determine how the scores from the Hexad user types would vary after six months, therefore, indicating the patterns of associations between the user types over time. The research model of our study is presented with the adjusted R^2 values in Figure 4 and the PLS path coefficients in Table 20.

The R^2 determines the impact of an independent variable on a dependent variable (MATTHEW *et al.*, 2021), defining the proportion of variance of the dependent variable explained by the independent variables (NAGELKERKE *et al.*, 1991). Since the R^2 increases depending on the number of predictors, we calculated the adjusted R^2 which is a modified version of R^2 that adjusts the number of predictors in a regression model. The adjusted R^2 indicated that in the second phase of the study, the variance on the Achiever user type score was 9% explained by the scores from the first phase of the study; the variance on the Disruptor user type score was

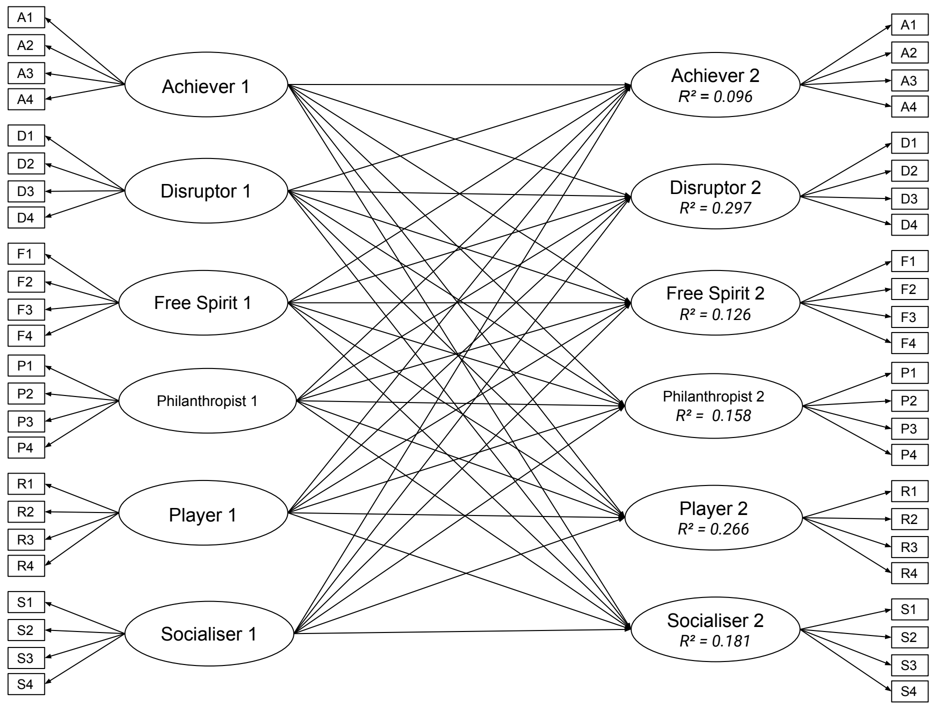


Figure 4 – Research model (study 4)

29% explained by the scores from the first phase of the study; the variance on the Free Spirit user type score was 12% explained by the scores from the first phase of the study; the variance on the Philanthropist user type score was 15% explained by the scores from the first phase of the study; the variance on the Player user type score was 26% explained by the scores from the first phase of the study; and the variance on the Socialiser user type score was 18% explained by the scores from the first phase of the study.

We also measured the F^2 to find the effect size of constructs. The F^2 represents the change in R^2 when an exogenous variable is removed from the model. We found small ($F^2 \geq 0.02$) and medium ($F^2 \geq 0.15$) effect sizes for most of the user types, excepting Disruptor and Player sub-scales that presented large effect sizes ($F^2 \geq 0.35$) (COHEN, 2013). The F^2 results can be seen in Table 19.

Table 19 – Effect Size (F^2) - (study 4)

	Achiever2	Disruptor2	Free Spirit2	Philanthropist2	Player2	Socialiser2
Achiever1	0.005	0.002	0.002	0.059	0.035	0.077
Disruptor1	0.013	**0.359**	0.008	0.002	0.000	0.002
Free Spirit1	0.046	0.004	0.074	0.029	0.004	0.002
Philanthropist1	0.054	0.016	0.028	0.070	0.065	0.010
Player1	0.027	0.005	0.004	0.008	**0.326**	0.003
Socialiser1	0.022	0.003	0.017	0.024	0.015	0.145

Key: Bold values are large effect sizes; Gray values are small effect sizes; 1: first research phase; 2: second research phase.

The values of the PLS path coefficients can vary between -1 and 1, with values closer to 0 representing weaker positive relationships and values closest to 1 reflecting the strongest positive relationships (HAIR *et al.*, 2016; GARSON, 2016). When considering only the associations between the same user type with the scores of both phases, our results indicated that the lowest and non-significant associations happened between the Achiever1 - Achiever2 (β = 0.087) and the Free Spirit1 - Free Spirit2 (β = 0.310). The other user types presented higher and significant associations (Philanthropist1 - Philanthropist2 (β = 0.327*), Player1 - Player2 (β = 0.583***), Socialiser1 - Socialiser2 (β = 0.433***), and Disruptor1 - Disruptor2 (β = 0.545***)) however, all the associations were under 0.7. When considering the significant associations between the user types, Philanthropist2 was negatively associated with Achiever1 (β = -0.296*); Socialiser2 was negatively associated with Achiever1 (-0.336*); Achiever2 was negatively associated with Philanthropist1 (-0.299*); and Player2 was negatively associated with Philanthropist1 (-0.295*).

4.2.3 Discussion

In this study, we focused on conducting further analysis on how the Hexad user types (*i.e.*, Achiever, Disruptor, Free Spirit, Philanthropist, Player, and Socialiser) change over time and how we could model user profiles based on these changes. Conducting different statistical analyses, we analyzed how the profile of 118 participants changed after six months, which of the main results indicated that most of the participants presented changes in their dominant user type over time. Furthermore, the scores in the six Hexad user types were different after six months and analysis of associations between the phases' scores indicated that the lowest association between the phases was presented in the Achiever user type sub-scale.

The distribution of the Hexad user types scores (presented in Table 17) indicated that our sample distribution followed other recent studies that used the Hexad model (TONDELLO *et al.*, 2019; ŞENOCAK; BÜYÜK; BOZKURT, 2019; MANZANO-LEÓN *et al.*, 2020; TASKIN; ÇAKMAK, 2020; ALTMEYER *et al.*, 2020b) when indicating that respondents present high scores in the Achiever and Philanthropist sub-scales and lower scores in the Disruptor sub-scale. Therefore, our results corroborate prior research indicating that Achievers and Philanthropists are the most common dominant user types and Disruptors the least common dominant user type. Overall, the Hexad user types that are intrinsically motivated presented a higher score in our results, which was also similarly found in prior research (FISCHER; HEINZ; BREITENSTEIN, 2018; TONDELLO *et al.*, 2019; OOGE *et al.*, 2020; MANZANO-LEÓN *et al.*, 2020). When comparing the Δ values from both phases of the study (see Table 17), there was a little difference in the scores, which was a first indication of changes in the user types. Even though the differences in the scores can be considered small, we understand that some participants may have increased a certain item while others dropped it, resulting in offsetting change in the final user type score.

The analysis considering only the dominant user type indicated that 72% of the participants showed a change in their dominant user types between the phases. As presented in Table 16, some of the user types combinations have presented significant changes between the phases of the study (*e.g.*, the combination of Achiever/Philanthropist dropping of 14% to 6% in

Table 20 – PLS-PM path coefficients (study 4)

	β	p-value	CI 2.5%	CI 97.5%
Achiever1 → Achiever2	0.087	0.696	-0.331	0.508
Achiever1 → Disruptor2	-0.049	0.706	-0.348	0.169
Achiever1 → Free Spirit2	0.051	0.787	-0.287	0.453
Achiever1 → Philanthropist2	**-0.296***	0.050	-0.593	-0.002
Achiever1 → Player2	-0.215	0.128	-0.478	0.093
Achiever1 → Socialiser2	**-0.336***	0.035	-0.639	-0.002
Disruptor1 → Achiever2	-0.117	0.379	-0.363	0.144
Disruptor1 → Disruptor2	**0.545*****	0.000	0.322	0.692
Disruptor1 → Free Spirit2	0.090	0.426	-0.151	0.297
Disruptor1 → Philanthropist2	-0.040	0.709	-0.242	0.177
Disruptor1 → Player2	0.015	0.864	-0.159	0.191
Disruptor1 → Socialiser2	0.041	0.682	-0.152	0.241
Free Spirit1 → Achiever2	0.248	0.184	-0.153	0.555
Free Spirit1 → Disruptor2	0.062	0.615	-0.189	0.290
Free Spirit1 → Free Spirit2	0.310	0.057	-0.106	0.555
Free Spirit1 → Philanthropist2	0.192	0.148	-0.108	0.405
Free Spirit1 → Player2	0.064	0.582	-0.200	0.265
Free Spirit1 → Socialiser2	0.051	0.721	-0.228	0.320
Philanthropist1 → Achiever2	**-0.299***	0.034	-0.598	-0.060
Philanthropist1 → Disruptor2	-0.142	0.303	-0.415	0.125
Philanthropist1 → Free Spirit2	-0.212	0.099	-0.473	0.016
Philanthropist1 → Philanthropist2	**0.327***	0.010	0.008	0.527
Philanthropist1 → Player2	**-0.295***	0.012	-0.554	-0.088
Philanthropist1 → Socialiser2	0.119	0.285	-0.083	0.346
Player1 → Achiever2	0.186	0.310	-0.251	0.464
Player1 → Disruptor2	0.073	0.484	-0.107	0.302
Player1 → Free Spirit2	0.070	0.617	-0.192	0.349
Player1 → Philanthropist2	-0.095	0.461	-0.350	0.145
Player1 → Player2	**0.583*****	0.000	0.365	0.770
Player1 → Socialiser2	-0.055	0.571	-0.231	0.151
Socialiser1 → Achiever2	0.176	0.197	-0.118	0.407
Socialiser1 → Disruptor2	-0.061	0.557	-0.245	0.179
Socialiser1 → Free Spirit2	0.154	0.189	-0.080	0.385
Socialiser1 → Philanthropist2	0.178	0.111	-0.045	0.395
Socialiser1 → Player2	0.130	0.166	-0.052	0.315
Socialiser1 → Socialiser2	**0.433*****	0.000	0.195	0.610

Key: Bold values are significant associations; * p<0.05, *** p<0.01; β: Regression Coefficient; CI: Confidence Interval; 1: first research phase; 2: second research phase.

the second phase). It is also notable that in both study phases, some combinations of user types have completely changed (*e.g.*, Player/Socialiser did not appear in the first phase of the study while 3% of the sample presented this user type as dominant in the second phase of the study). When analyzing the correlations presented between both phases using Kendall's τ test (see

Table 17), even though all of them were significant, they were weak and moderate correlations. These might indicate that some user types might be more stable over time than others, findings that are consistent with prior research (BUSCH *et al.*, 2016; YILDIRIM; ÖZDENER, 2021). Therefore, our results indicate that users present changes in their dominant user type over time and consequently the dominant user types from the Hexad model can not be considered stable.

Based on these indications of changes, we also analyzed how much the dominant user types changed considering the demographic data and gaming habits of the participants. The changes considering the age groups, educational levels, and gaming habits demonstrated that it can be difficult to find patterns of change when considering these characteristics. Half of the age groups measured in this study presented a change of more than 70%, which might be an indication that changes can happen during all life stages. Only participants from one age group (50 to 54 years old) presented 100% of change in their dominant user types, while none of the participants from the oldest group (older than 60 years old) presented changes. Considering age and the Hexad user types, prior research has indicated that there is a tendency for user types derived from intrinsic motivations (*i.e.*, Achiever, Philanthropist, Free Spirit, and Socialiser) to increase with age (ALTMEYER; LESSEL, 2017; TONDELLO *et al.*, 2019). Aligned with our results, this might indicate that, differently from personality traits, gamification user types might not reach a stability level after some age.

When we consider the educational level of the participants, people that self-reported being in Elementary/Middle/High School changed less (68%) than others. Overall, the percentage of changes was very similar, especially considering the groups that self-reported to have a Bachelor, MBA, M.Sc., or Ph.D. degree. This might indicate that the educational level of the respondents does not influence the changes in their user types. Regarding gaming habits, people who self-reported not playing games changed more their dominant user types than people who self-reported playing games as a habit. Prior studies (POECZE; RONCEVIC; ZLATIC, 2019; SENOCAK; BÜYÜK; BOZKURT, 2021) indicated that some user types from Hexad could present different gaming preferences from others. This relationship between user types and gaming habits might explain why people who have gaming as a habit have more stable user types over time.

To conduct a deeper analysis, considering that the users are motivated by all the Hexad tendencies (TONDELLO *et al.*, 2019; ALTMEYER *et al.*, 2019b), and the dominant user type might not be sufficient to differentiate users' preferences (HALLIFAX *et al.*, 2019b), we conducted a statistical analysis between the scores of each sub-scale in both research phases using PLS-PM. The lower association was presented between the scores of the Achievers (β = 0.087), thus we can conclude that the scores of the Achiever sub-scale were the ones that presented more differences when comparing both phases of the study. Since this user type is considered one of the prevalent user types (TONDELLO *et al.*, 2016; TONDELLO *et al.*, 2019; ALTMEYER *et al.*, 2020b), (*e.g.* people usually present a high average score in its sub-scale), this result might indicate why static personalization could present mixed or negative results over time, and highlight the necessity of constant analysis of the users' profiles.

Excepting the Free Spirit user type (β = 0.310), all the other user types presented significant associations between the scores of both phases. Philanthropists (β = 0.327*) and Socialisers (β = 0.433***) presented associations bellow 0.5 while Players (β = 0.583***) and Disruptors (β = 0.545***) presented associations higher than 0.5. These results indicated that scores from user types derived from extrinsic motivations (*i.e.*, Player and Disruptor) present a stronger association after six months than scores from user types derived from intrinsic motivations (*i.e.*, Achiever, Philanthropist, Socialiser, and Free Spirit). Therefore, our results indicate that people who have high scores in the user types with extrinsic motivation can present more stable user types over time.

Considering all the associations, our results indicate that Philanthropists in the first phase of the research presented a significant negative association with the Player (β = -0.295*) and Achiever (β = -0.299*) user types' second scores. Philanthropists presented negative associations with four of the five other user types' scores in the second phase and also presented the second highest correlation between phases considering Kendall's τ test (0.418*). Besides being the highest dominant user type score in our sample in the first and second phase of the study, Philanthropist was present in other 13 combinations of dominant user types (*i.e.*, they were the highest score of the participants however, the participants had the same score repeated in other user types) in the first phase and second phase of the study. Besides corroborating prior research that has indicated them as a prevalent user type overall (FISCHER; HEINZ; BREITENSTEIN, 2018; MANZANO-LEÓN *et al.*, 2020), the association results from PLS analyses might indicate that Philanthropists are the most stable user type when considering only the user types derived from intrinsic motivation.

The Achiever user type in the first phase of the research presented negative and significant associations with the scores from Philanthropist (β = -0.296*) and Socialiser (β = -0.336*) in the second phase of the research. They also presented a negative association with Disruptor (β = -0.049) and Player (β = -0.215) scores from the second phase. Overall, this user type presented the highest changes in the scores' means between the phases (Δ = 0.95) and the second lowest correlation between phases considering Kendall's τ test (0.301*). Thus, even though being considered one of the prevalent user types in the Hexad Model (TONDELLO *et al.*, 2016; TONDELLO *et al.*, 2019; ALTMEYER *et al.*, 2020b), we understand that this user type can be considered the less stable user type from the Hexad model. Considering the association between Achievers' first score and Free Spirits' second score (β = 0.051) and Free Spirits' first score and Achievers' second score (β = 0.248), we believe that people who score higher in the Achiever sub-scale, over time tend to decrease their score in this sub-scale and increase in the Free Spirit items.

4.2.4 Recommendations on how to model user types

As outlined, after six months the user types from the Hexad model can not be considered stable. The majority of the participants presented different dominant user types after six months and the average scores of the user types also differed in both phases, indicating that some user types are more stable than others. Our findings demonstrated that when modeling user profiles based on Hexad user types, it is critical to evaluate the user types after a certain period of time to track how the users change over time. The personalization of gamified environments must also adapt to the user's changing, ensuring that the personalization continues to support the user.

Considering user type and age, our results indicate that there is no pattern of change and they can happen during all life stages. As prior research has indicated that people might have the tendency to increase their scores in user types derived from intrinsic motivations while getting older (ALTMEYER; LESSEL, 2017; TONDELLO *et al.*, 2019), is also important to evaluate the user types of the users before completing six months of the first measurement. Our results indicated that only considering the educational level of the users might not be the best strategy to create personalized gamified environments, since the educational level of the respondents seems to not indicate patterns of change in their dominant user types after six months. When considering our results and prior research that has shown that gaming habits might have a relationship with some user types (POECZE; RONCEVIC; ZLATIC, 2019; SENOCAK; BÜYÜK; BOZKURT, 2021), it would be important to evaluate with frequency the user types from people that do not have gaming habits.

Considering the results of the changes based on the Hexad user types, to develop or adapt gamified environments to people that have high scores in the Socialiser user type, researchers and designers should consider initially implementing game elements that are considered most suitable for this user type and over time also starting to implement game elements that are suitable for Achievers, Philanthropists, and Free Spirit. For people that have high scores in the Free Spirit user type, researchers and designers should consider initially implementing game elements that are considered most suitable for this user type and over time start to implement game elements that are also indicated for Achievers. Moreover, our results demonstrated that people with high intrinsic motivation might be less stable over time. Therefore, designers and researchers should measure the user types from people who present high scores in the Socialiser, Achiever, Philanthropist, and Free Spirit subscale before completing six months of the first measurement. In Table 21 we summarize these recommendations of how to model user types considering the results found in this study.

4.2.5 Limitations and opportunities for future studies

During its conduction, this study has presented some limitations concerning different aspects. Our study was able to collect a limited number of responses from participants of only one country (*i.e.,* Brazil), which might prevent the generalization of the results. Therefore, the

Table 21 – Recommendations on how to model user types (study 4)

	Recommendation
Age	Changes in the user type can happen during all life stages, therefore, the user profile should be evaluated before completing six months of the first measurement and then being measured with regularity.
Gaming Habits	People who do not have gaming habits seem to present less stable user types over time. Their profile should be evaluated before completing six months of the first measurement.
Philanthropist	This user will continue to present higher scores in the Philanthropist user type after six months, however, can also increase a little their Socialiser tendencies.
Achiever	This user will probably present a higher score in the Free Spirit user type after six months.
Player	This user will maintain a high score in the Player user type but can also increase a little in the Achiever tendencies. This user type is probably one of the most stable over time.
Free Spirit	Will tend to maintain a high score in the Free Spirit user type but also increase in the Achiever tendencies over time.
Socialiser	Will tend to maintain a high score in the Socialiser user type however, can increase the Philanthropist, Achiever, and Free Spirit tendencies over time.
Disruptor	Will tend to maintain a high score in the Disruptor user type. This user type is probably one of the most stable over time.

results here presented might not be the same considering other samples. When constructing the survey, we used limited options of gender (*i.e.,* men, women, other, and preferred not to answer). The use of the term "other" can be considered offensive to people who are already marginalized in society (SPIEL; HAIMSON; LOTTRIDGE, 2019). By using a binary option to collect gender, we also prevented ending up with insights about how to model user profiles considering this user characteristic. In addition, we understand that this limitation could lead some respondents to not properly answer the survey or leave the study without submitting responses.

Overall, the use of surveys to collect responses has been indicated as a research limitation in the field (KLOCK *et al.*, 2020; KIMPEN *et al.*, 2021; RODRÍGUEZ; PUIG; RODRIGUEZ, 2021). The use of surveys (or questionnaires), can lead to the collection of inaccurate data, directly influencing the study's results. Therefore, the use of surveys might not be the most suitable option to evaluate the respondents' user types.

Regarding the data collected, when considering the age reported by the participants, the groups in our sample did not have the same size, *e.g.*, 12% of the participants were placed in the 40-44 years old group while only 1% of the participants were older than 60 years. This might have directly impacted the results by age, which indicated no patterns of change and that changes happen during all life stages. This result might not remain the same when using homogeneous samples.

Based on the results and limitations of this study, it is possible to suggest new studies that could further the understanding of user profiles in gamified environments. Prior research (ALTMEYER; LESSEL, 2017; TONDELLO *et al.*, 2019) have indicated that age could directly affect the chances of a person having an intrinsically motivated user type (*i.e.*, Achiever, Philanthropist, Socialiser, and Free Spirit). However, these studies did not make comparisons of the same group over time, instead, they compared the age of the participants (TONDELLO *et al.*, 2019) or different samples (ALTMEYER; LESSEL, 2017). Our results demonstrated that it can be difficult to find patterns of change when considering age as the main user characteristic. At the same time, one limitation of our study is that the age groups were not equivalent (*i.e.*, some age groups had more participants than others). To better analyze how well age influences the user type over time, as well as, to better create recommendations on how to model user types based on age, we suggest the conduction of studies where the number of participants in each age group is the same, therefore, increasing the possibility of finding patterns on how age influences the user types changes.

When defining the user profile, we used the Gamification Hexad user type as the main user aspect that should be considered as their profile and only included gender, age, educational level, and gaming habits as other factors that could impact the changes. This decision was made considering that these users' characteristics are currently the most researched users' aspects of gamification. However, besides the influence contexts or tasks can present when defining user profiles, prior research (KLOCK *et al.*, 2020) has indicated a need for gamification research of a broader sample of user characteristics that goes beyond the dominant user type or the binary biological sex. We suggest that future studies about the stability of user profiles consider the user profile as a group of different user aspects, rather than using only the dominant characteristics, analyzing how other less dominant characteristics can influence the user profile changes.

4.2.6 Summary

In this study, divided into two different phases, we conducted a comparison of how 118 people's user types have presented changes after six months. The goal of this comparison was to identify how the user types from the Gamification User Types Hexad (Achiever, Philanthropist, Socialiser, Free Spirit, Player, and Disruptor) present changes over time, as well as how we could model user profiles based on these changes. Our initial results showed that the dominant user type of most of the participants presented changes after six months, and furthermore, the average scores of the user types in both phases were also different, indicating that neither the dominant user types nor tendencies can be considered stable. By using a set of different statistical analyses, our results indicated that the Achiever might be the less stable user type and Player the most stable user type from the Hexad model. Based on our results, we indicate a set of recommendations on how to model user types based on their changes. Moreover, our results indicated insights into how the user types change based on their educational level, age group, and gaming habits. Our results implicate that when designing a gamified environment based on the Hexad user type, it is important to develop a design that can support the user type's changes after a certain period of time.

4.3 Chapter conclusion

To the best of our knowledge, these were the first studies that measured the stability of the Hexad user types, analyzed how the user types change after six months, and how to model based on these changes. Both studies indicated that people can present different dominant user types after six months, and also the differences in the average scores of the user types indicated that even the less dominant user types change over time. Some topics of the research agenda indicated in the first study are already being addressed by the community *e.g.*, Yildirim and Ozdener (YILDIRIM; ÖZDENER, 2021) that analyzed the stability of the Hexad user types considering a specific domain (*i.e.*, the educational context).

Therefore, these studies indicated to the gamification community the importance of developing a design that can support user type changes in a gamified environment. Consequently, to guarantee that the personalization supports the user constantly, the personalization of gamified environments also needs to track the user's changes.

CHAPTER

5

GAMIFICATION DESIGN BASED ON THE HEXAD USER TYPES AND OTHER USERS' CHARACTERISTICS

This chapter presents two studies conducted with the general objective of analyzing the preferences for gamification designs considering the Hexad user types. The first study (see Appendix B) analyzed whether the preferences over game elements and perceived sense of accomplishment in gamification designs are different considering the Hexad user types, and it was published in User Modeling and User-Adapted Interaction (SANTOS *et al.*, 2021b). The second study analyzed the relationship between Hexad user types and other demographic characteristics, as well as how to personalize gamified environments based on this relationship. This second study is, up to date, under review at the same journal (*i.e.*, User Modeling and User-Adapted Interaction from Springer).

5.1 The relationship between the Hexad user types and gamification designs

Although in the past few years, researchers have conducted some studies about personalized gamification (HALLIFAX *et al.*, 2019a; KLOCK *et al.*, 2020; RODRIGUES *et al.*, 2020), they have not reached a consensus about which game elements would be the most suitable for each player/user type, have used a small number of game elements, or have analyzed the relation of user types and game elements individually (HALLIFAX *et al.*, 2019b; KLOCK *et al.*, 2020). The relation between user types and sets of game elements demonstrated in the study conducted by Tondello *et al.* (TONDELLO *et al.*, 2016) showed that the user types could be related with sets of game elements, rather than individual game elements. Thus, one gap in the personalized gamification field are studies about the preference for gamification designs (sets of game elements grouped according to their characteristics or purpose) for each user type, and if they are positively affected by these gamification designs. Also, when we consider the way that the game elements are selected, most of the studies about personalized gamification select the game elements deliberately or by using literature reviews, which can bring some limitations (*e.g.*, the use and random naming of game elements that are correlated, or the exclusion of a game element that would be suitable for the context) (KLOCK *et al.*, 2020; RODRIGUES *et al.*, 2020).

Considering these literature gaps, we conducted a study where we *i)* identified the participants' user types, *ii)* analyzed their preferences regarding different gamification designs (represented in storyboards and with game elements selected from a taxonomy specifically developed for the education context (TODA *et al.*, 2019a)), *iii)* measured the participants' preference and perceived sense of accomplishment in each gamification design, and *iv)* analyzed how the participants' preferences and perceived sense of accomplishment are associated with their user types. The study's results allow us to move towards evidence-based gamification design, generating new insights for gamification designers to create more effective gamified systems according to the users' preferences and experiences. In this study, we also provided a series of validated storyboards to represent the design concept of a personalized gamified educational system.

5.1.1 Method, data collection, and participants

This study aimed to identify whether the user types affect the preference and perceived sense of accomplishment for gamification designs. Thus, our research question was: "How are user types (Philanthropist, Achiever, Socialiser, Free Spirit, Player, and Disruptor) associated with preference and perceived sense of accomplishment in different gamification designs (Fictional, Personal, Performance, Social, and Ecological)?". To answer our research question, we organized this study in three different steps: *i)* storyboards' design and evaluation; *ii)* survey application; and *iii)* data analysis.

To select the game elements of the study, we used Toda's taxonomy (TODA *et al.*, 2019a) that is, as far as we know, the only one that has been developed and validated for the educational context, explaining a considerable number of game elements, and grouping them into dimensions. Toda's taxonomy (TODA *et al.*, 2019a) is composed of twenty-one game elements organized into five dimensions: the *Performance/Measurement* dimension is related to the environment response and has the elements Point, Progression, Level, Stats, and Acknowledgement; the *Ecological* dimension is related to the environment that the gamification is being implemented in and is formed by the elements Chance, Imposed Choice, Economy, Rarity, and Time Pressure; the *Social* dimension is related to the interactions between the learners presented in the environment and has the elements Competition, Cooperation, Reputation, and Social Pressure; the *Personal* dimension is related to the learner that is using the environment and has the elements Sensation, Objective, Puzzle, Novelty, and Renovation; and the *Fictional* dimension is the mixed dimension that is related to the user and the environment and has the elements Narrative and Storytelling.

As recommended in recent literature in the field of Human-Computer Interaction (HCI) (ORJI; VASSILEVA; MANDRYK, 2014; ALTMEYER *et al.*, 2019a; ALTMEYER *et al.*, 2020a; YASSAEE; METTLER; WINTER, 2019), the use of storyboards, a graphical depiction of a narrative (TRUONG; HAYES; ABOWD, 2006), is a good strategy that can be used in HCI and design to illustrate interfaces and contexts of use, thus offering designers a possibility as a prototyping technique. The use of storyboards can help users perceive and interpret proposed functionalities (TRUONG; HAYES; ABOWD, 2006), and also help to direct the respondents' focus (YASSAEE; METTLER; WINTER, 2019). Given the benefits storyboards offer to collect user reactions to the system elements (TRUONG; HAYES; ABOWD, 2006), they can help with the collection of data from people with different backgrounds since they provide a visual language that facilitates user understanding (ORJI; TONDELLO; NACKE, 2018), and that other recent gamification studies have used storyboards (ALTMEYER *et al.*, 2019a; YASSAEE; METTLER; WINTER, 2019; ALTMEYER *et al.*, 2020a), we decided to implement five storyboards to represent each of the five dimensions proposed in Toda's taxonomy (TODA *et al.*, 2019a).

To design the storyboards, we followed the recommendations of Truong *et al.* (TRUONG; HAYES; ABOWD, 2006), which have been successfully used in recent similar studies (*e.g.*, (ORJI; MANDRYK; VASSILEVA, 2017; ALTMEYER *et al.*, 2019a; BRENES; MARÍN-RAVENTÓS; LÓPEZ, 2019)). Truong *et al.* (TRUONG; HAYES; ABOWD, 2006) determined five attributes to design a storyboard: *i)* Level of detail; *ii)* Inclusion of text; *iii)* Inclusion of people and emotions; *iv)* Number of frames; and *v)* Portrayal of time. Thus, we created five storyboards with six frames each, representing a fictional learning environment without defining a specific curricular component. All of the 21 game elements of Toda's taxonomy (TODA *et al.*, 2019a) were used in the storyboards according to their dimension. Also, considering the own organization of the taxonomy to avoid overlapping, each one of the 21 game elements was represented only in one storyboard. The storyboards were evaluated by three gamification experts with extensive experience in evaluating this type of technology, to guarantee that the storyboards correctly represented the five dimensions proposed by Toda *et al.* (TODA *et al.*, 2019a). The storyboards and their textual description can be seen in Santos *et al.* (SANTOS *et al.*, 2021b) and Appendix B.

To collect the data for this study, we employed an online survey through the platform Google Forms, consisting of three sections: (i) demographic data (age, gender (options were: male, female, other, and I prefer to not inform), educational level, state (options were the 26 Brazilian states and the Federal District)), and gaming habits (if the respondent play games and the frequency (options were: every day, every week, rarely, and I do not know)), (ii) the Hexad scale (composed of 24 statements, four items for each sub-scale), and (iii) sense of accomplishment (eight statements) and preference for gamification designs. To measure the Hexad user types of the participants, we used the scale analyzed on section 3.1, where the items were randomly presented on a 7-point Likert scale (LIKERT, 1932), and we also included an "attention-check" statement to check if people were paying due attention when reading and answering the form. Responses from people who missed the attention-check statement were removed from the data analysis. In the third section of the survey, we used the sub-scale proposed by Högberg *et al.* (HÖGBERG; HAMARI; WÄSTLUND, 2019) to measure the perceived sense of accomplishment.

Accomplishment is part of the gameful experience users can have in gamified systems. Högberg *et al.* (HÖGBERG; HAMARI; WÄSTLUND, 2019) identified seven dimensions that can describe the gameful experience: Accomplishment, Challenge, Competition, Guided, Immersion, Playfulness, and Social experiences. The accomplishment dimension is defined as experiencing the demand for successful performance, goal achievement, and progress (HÖGBERG; HAMARI; WÄSTLUND, 2019). Users can be motivated to complete a goal or task for the pleasure of feeling accomplished, as there is a specific type of intrinsic motivation that leans towards accomplishment (VALLERAND *et al.*, 1992; BARKOUKIS *et al.*, 2008). In our study, we focused on the measurement of this dimension because it can reflect the users' engagement and can be considered as a long-term experience that extends beyond the use of the service, which can be essential to achieving the goal of gamification (HÖGBERG; HAMARI; WÄSTLUND, 2019).

Following Högberg *et al.* (HÖGBERG; HAMARI; WÄSTLUND, 2019) recommendations, the respondents were asked to rate on a 7-point Likert scale (LIKERT, 1932) how well each of the eight statements of the Accomplishment dimension represented their feelings about each gamification design. Besides the measurement of the perceived sense of accomplishment, the last question of the survey was "Which storyboard is your favorite?". Thus, we were able to compare the perceived sense of accomplishment with the respondent's preference for the gamification designs.

The final survey was spread by social networks and e-mail. The survey was open for thirty-eight days and we received 366 answers, of which 331 were valid according to our attention-check question. The respondents participated voluntarily since we did not offer any kind of remuneration or gifts to the respondents. The study sample size is adequate under different aspects considering this type of study. According to the definitions of Bentler and Chou (BENTLER; CHOU, 1987) and Hair *et al.* (HAIR *et al.*, 1998), it is necessary to have at least five participants for each construct measured (our study had seven constructs). Loehlin (LOEHLIN, 1998) suggests a minimum sample of 100 participants for studies of this nature. Table 22 presents the demographic information of the respondents.

Table 23 summarizes the participants' distribution by the dominant user types (*i.e.*, the strongest tendency of the participants), the average scores, and the standard deviation for each Hexad user type. Resembling other recent studies (TONDELLO *et al.*, 2019; ŞENOCAK; BÜYÜK; BOZKURT, 2019; MANZANO-LEÓN *et al.*, 2020; TASKIN; ÇAKMAK, 2020;

Table 22 – Demographic information of participants (SANTOS *et al.*, 2021b)

	Variable	%		Variable	%
Gender	Female	52%	**Age**	10 - 14	0.30%
	Male	47%		15 - 19	9%
	Other	0.60%		20 - 24	12%
	Preferred not to answer	0.60%		25 - 29	15%
Education Level	Elementary/Middle School	2%		30 - 34	18%
	High School	9%		35 - 39	13%
	Bachelor	30%		40 - 44	12%
	Specialized Courses	21%		45 - 49	10%
	M.Sc.	25%		50 - 54	7%
	PhD	8%		55 - 59	4%
	PostDoc	4%		Over 60	1%
Gaming Habits	Play games	67%	**Frequency**	Every day	13%
				Every week	21%
				Rarely	47%
				I do not know	19%
	Do not play games	33%			

ALTMEYER *et al.*, 2020b), our research identified that Philanthropist and Achievers are the most common dominant user types and Disruptor is the least common dominant user type. Comparing the women's and men's scores in each of the Hexad user types, it is possible to identify that the men scored were higher than women in all of them.

Table 23 – Participants distribution, average scores, and standard deviation (SANTOS *et al.*, 2021b)

User Types	D	Mean score	S.D.	Female Mean Score	S.D.	Male Mean Score	S.D.
Philanthropist	35%	24.18	4.78	23.86	5.47	24.50	3.89
Achiever	30%	23.98	4.79	23.41	5.60	24.57	3.61
Free Spirit	12%	22.50	4.63	22.23	5.30	22.71	3.74
Player	12%	20.53	5.61	19.76	5.96	21.37	5.05
Socialiser	10%	20.42	5.7	20.49	6.03	20.51	5.22
Disruptor	1%	14.66	5.33	13.91	5.48	15.32	4.98
Key: D: Distribution of the dominant user types; S.D.: standard deviation							

5.1.2 Results

Initially, we analyzed the data normality using the Shapiro-Wilk test as recommended by Wohlin *et al.* (WOHLIN *et al.*, 2012), which showed that our data followed a non-normal distribution. Then, we measured the internal reliability for each Hexad sub-scale (user types in the survey), as well as for the perceived sense of accomplishment evaluation in each storyboard. Overall, the reliability was acceptable ($\alpha \geq 0.70$, Jöreskog's Rho (RHO A) ≥ 0.70, CR ≥ 0.70, Average Variance Extracted (AVE) ≥ 0.50) for all storyboards and user types, except for the Disruptors. We also measured the discriminant validity finding acceptable values, considering that the square root of the variables' AVE value was larger than the correlations that the variable had with the other variables, and all of the variables presented correlations between them below 0.85. The reliability results can be seen in Table 24 and the discriminant validity can be seen in Table 25.

Table 24 – Reliability results (SANTOS *et al.*, 2021b)

Construct	**Cronbach's α**	**Jöreskog's rho**	**Comp.R**	**Average V. E.**
Achiever	0.881	0.887	0.918	0.736
Disruptor	0.679	0.664	0.726	0.426
Free Spirit	0.755	0.768	0.845	0.578
Philanthropist	0.885	0.893	0.921	0.744
Player	0.880	0.886	0.918	0.737
Socialiser	0.808	0.818	0.874	0.635
SE	0.973	0.974	0.977	0.842
SF	0.962	0.964	0.968	0.791
SPF	0.974	0.974	0.977	0.844
SP	0.967	0.969	0.972	0.812
SS	0.977	0.978	0.980	0.859

Key: Comp.R: Composite Reliability; Average V. E.: Average Variance Extracted; SF: The perceived sense of accomplishment for the storyboard Fictional; SP: The perceived sense of accomplishment for the storyboard Personal; SPF: The perceived sense of accomplishment for the storyboard Performance; SE: The perceived sense of accomplishment for the storyboard Ecological; SS: The perceived sense of accomplishment for the storyboard Social.

Table 25 – Discriminant Validity (SANTOS *et al.*, 2021b)

	AccE	AccF	AccPF	AccP	AccS	A	D	F	P	R	PrE	PrF	PrPF	PrP	PrS	S
AccE	0.918															
AccF	0.474	0.889														
AccPF	0.614	0.550	0.919													
AccP	0.620	0.623	0.639	0.901												
AccS	0.652	0.545	0.638	0.574	0.927											
A	0.367	0.400	0.480	0.389	0.429	0.858										
D	0.209	0.246	0.255	0.262	0.254	0.499	0.653									
F	0.268	0.369	0.369	0.294	0.322	0.740	0.539	0.760								
P	0.353	0.385	0.441	0.385	0.386	0.771	0.398	0.696	0.862							
R	0.313	0.280	0.349	0.302	0.369	0.563	0.425	0.511	0.413	0.797						
PrE	0.054	-0.134	-0.134	-0.094	-0.045	-0.042	-0.078	0.015	0.002	-0.041	1.000					
PrF	-0.074	0.142	-0.130	0.017	-0.091	0.000	-0.079	-0.030	-0.021	0.010	-0.161	1.000				
PrPF	-0.003	-0.079	0.183	-0.070	-0.047	0.045	0.086	0.048	0.010	0.034	-0.343	-0.260	1.000			
PrP	0.030	0.037	0.030	0.135	-0.014	-0.008	-0.044	0.026	-0.025	0.096	-0.153	-0.116	-0.248	1.000		
PrS	-0.011	0.077	-0.011	0.053	0.165	-0.008	0.059	-0.061	0.019	-0.074	-0.273	-0.207	-0.441	-0.197	1.000	
S	0.306	0.444	0.364	0.356	0.451	0.559	0.310	0.541	0.665	0.393	-0.070	-0.024	-0.075	-0.048	0.192	0.858

Key: P: Philanthropist; A: Achiever; R: Player; F: Free Spirit; S: Socialiser; D: Disruptor; AccE: Perceived sense of accomplishment for the storyboard Ecological; AccF: Perceived sense of accomplishment for the storyboard Fictional; AccPF: Perceived sense of accomplishment for the storyboard Performance; AccP: Perceived sense of accomplishment for the storyboard Personal; AccS: Perceived sense of accomplishment for the storyboard Social; PrE: Preference Ecological; PrF: Preference Fictional; PrPF: Preference Performance; PrP: Preference Personal; PrS: Preference Social.

Table 26 presents the preference and perceived sense of accomplishment averages in general and by gender. It was possible to identify that the Performance gamification design was the most chosen in terms of preference and perceived sense of accomplishment.

To answer our research question and measure the effects of the personalized gamification designs in terms of sense of accomplishment and preference, following other recent studies in the

Table 26 – Comparison between the favorite storyboard and the perceived sense of accomplishment (SANTOS *et al.*, 2021b)

Storyboard	Preference	Accomplishment	Female Acc	Male Acc
Fictional	11%	14%	15%	13%
Personal	10%	12%	13%	11%
Performance	36%	28%	27%	30%
Ecological	18%	21%	20%	22%
Social	26%	25%	25%	25%

Key: Preference: Which storyboard did you prefer?; Accomplishment: The perceived sense of accomplishment; Female Acc: The perceived sense of accomplishment by women; Male Acc: The perceived sense of accomplishment by the men

personalized gamification field (ORJI; TONDELLO; NACKE, 2018; HALLIFAX *et al.*, 2019b; HALLIFAX; LAVOUÉ; SERNA, 2020), we employed the Partial Least Squares Path Modeling (PLS-PM) analysis to identify the relation between the Hexad user types with the gamification designs, since it is a reliable method for estimate cause-effect relationship models with latent variables (HAIR *et al.*, 2016). The research model of our study can be seen in Figure 5.

The results indicated that the Achievers were positively associated with a perceived sense of accomplishment from the Performance (β = 0.295***) and Social (β = 0.238*) designs. Players were positively associated with a perceived sense of accomplishment from Ecological (β = 0.162*) and Social (β = 0.161*) designs; positively associated with preference from Personal (β = 0.165**) design and negatively associated with preference from Social (β = -0.148*) design. Free Spirits were only negatively associated with preference from Social (β = 0.150*) design. Socialisers were positively associated with a perceived sense of accomplishment from Fictional (β = 0.307***), Personal (β = 0.154*), and Social (β = 0.309***) designs; positively associated with preference from Social (β = 0.370***) design, and negative associated with preference from Performance (β = -0.165*) design. Disruptors were positively associated with preference from Social (β = 0.150*) design. Finally, Philanthropists did not present any association. All the associations can be seen in Table 27.

5.1.3 Discussion

In terms of the user type distribution, our results (see Table 23) are similar to prior research, with Philanthropist as the most common dominant user type and Disruptor as the least common dominant user type. According to Tondello *et al.* (TONDELLO *et al.*, 2019), women tend to score higher than men in all the user types with intrinsic motivations (*i.e.* Philanthropist, Socialiser, Free Spirit, and Achiever), and even though in our results men scored higher than women in all the user types, the difference was smaller in the Philanthropist, Socialiser, Free Spirit, and Achiever types (*i.e.* the user types that are motivated intrinsically).

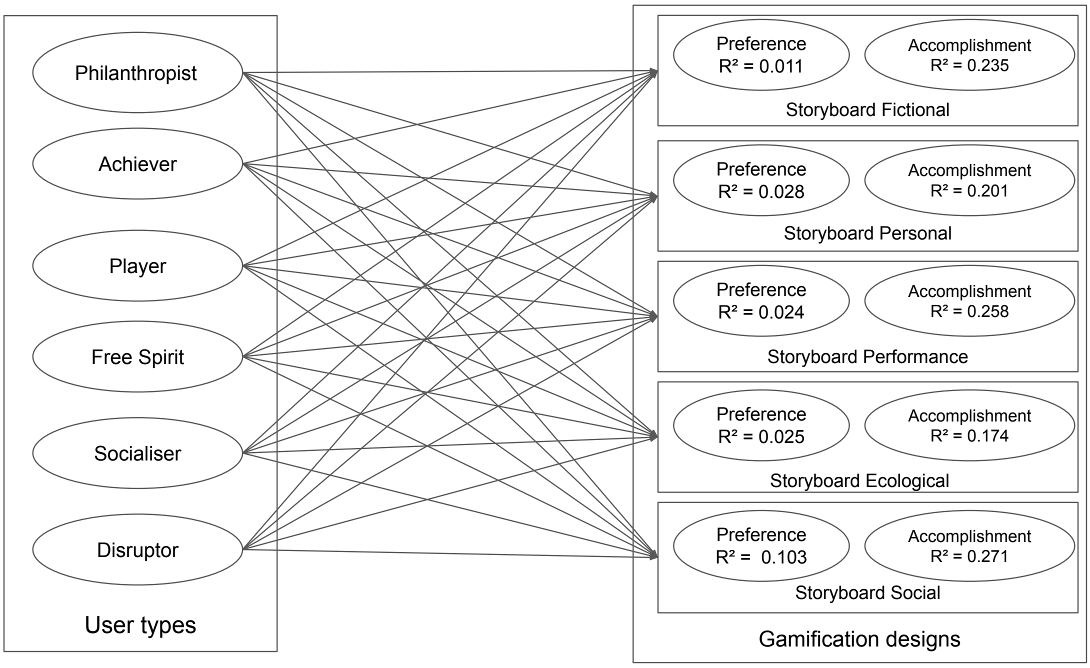
Starting to answer our research question, we identified different positive and negative

Table 27 – Associations between gamification designs and user types (SANTOS *et al.*, 2021b)

			CI					CI	
	β	*P-value*	2.5%	97.5%		β	*P-value*	2.5%	97.5%
PAcc → SF	-0.006	0.951	-0.176	0.198	AAcc → SF	0.157	0.110	-0.035	0.333
PPr → SF	-0.029	0.765	-0.214	0.172	APr → SF	0.080	0.444	-0.121	0.281
PAcc → SP	0.164	0.063	-0.029	0.342	AAcc → SP	0.168	0.066	-0.027	0.314
PPr → SP	-0.013	0.890	-0.209	0.171	APr → SP	-0.064	0.515	-0.234	0.105
PAcc → SPF	0.149	0.082	-0.028	0.304	AAcc → SPF	**0.295*****	0.001	0.119	0.456
PPr → SPF	0.020	0.852	-0.193	0.216	APr → SPF	0.047	0.667	-0.159	0.255
PAcc → SE	0.166	0.069	-0.004	0.338	AAcc → SE	0.174	0.075	-0.012	0.346
PPr→ SE	0.119	0.242	-0.086	0.317	APr→ SE	-0.113	0.315	-0.329	0.079
PAcc → SS	0.005	0.956	-0.146	0.176	AAcc → SS	**0.238***	0.011	0.049	0.420
PPr → SS	-0.095	0.309	-0.261	0.056	APr → SS	0.034	0.724	-0.143	0.214
RAcc → SF	0.030	0.627	-0.095	0.154	FAcc → SF	0.058	0.429	-0.082	0.206
RPr → SF	0.042	0.613	-0.115	0.182	FPr → SF	-0.021	0.804	-0.210	0.133
RAcc → SP	0.109	0.101	-0.031	0.241	FAcc → SP	-0.132	0.127	-0.291	0.062
RPr → SP	**0.165****	0.002	0.048	0.261	FPr → SP	0.104	0.261	-0.093	0.298
RAcc → SPF	0.117	0.062	-0.004	0.230	FAcc → SPF	-0.063	0.351	-0.193	0.081
RPr → SPF	0.009	0.892	-0.124	0.123	FPr → SPF	0.040	0.661	-0.139	0.244
RAcc → SE	**0.162***	0.014	0.033	0.310	FAcc → SE	-0.124	0.142	-0.281	0.036
RPr→ SE	-0.005	0.946	-0.138	0.140	FPr→ SE	0.145	0.066	-0.032	0.276
RAcc → SS	**0.161***	0.012	0.021	0.291	FAcc → SS	-0.128	0.154	-0.299	0.037
RPr → SS	**-0.148***	0.031	-0.270	-0.008	FPr → SS	**-0.226****	0.009	-0.386	-0.073
SAcc → SF	**0.307*****	0.000	0.171	0.437	DAcc → SF	0.031	0.644	-0.091	0.154
SPr → SF	-0.021	0.803	-0.190	0.127	DPr → SF	-0.108	0.189	-0.260	0.036
SAcc → SP	**0.154***	0.036	0.004	0.297	DAcc → SP	0.090	0.231	-0.055	0.239
SPr → SP	-0.092	0.284	-0.259	0.083	DPr → SP	-0.104	0.166	-0.250	0.030
SAcc → SPF	0.087	0.204	-0.042	0.231	DAcc → SPF	0.006	0.916	-0.085	0.123
SPr → SPF	**-0.165***	0.032	-0.305	-0.025	DPr → SPF	0.081	0.258	-0.072	0.223
SAcc → SE	0.094	0.186	-0.052	0.229	DAcc → SE	0.026	0.732	-0.115	0.174
SPr→ SE	-0.130	0.081	-0.270	0.005	DPr→ SE	-0.104	0.139	-0.222	0.025
SAcc → SS	**0.309*****	0.000	0.155	0.446	DAcc → SS	0.038	0.564	-0.077	0.165
SPr → SS	**0.370*****	0.000	0.259	0.467	DPr → SS	**0.150***	0.017	0.023	0.254

Key: * p<0.1, ** p<0.05, *** p<0.01; β: Regression Coefficient; CI: Confidence Interval; PAcc: Philanthropist perceived sense of Accomplishment; PPr: Philanthropist Preference; AAcc: Achiever perceived sense of Accomplishment; APr: Achiever Preference; RAcc: Player perceived sense of Accomplishment; RPr: Player Preference; FAcc: Free Spirit perceived sense of Accomplishment; FPr: Free Spirit Preference; SAcc: Socialiser perceived sense of Accomplishment; SPr: Socialiser Preference; DAcc: Disruptor perceived sense of Accomplishment; DPr: Disruptor Preference; SF: Storyboard Fictional; SP: Storyboard Personal; SPF: Storyboard Performance; SE: Storyboard Ecological; SS: Storyboard Social.

Figure 5 – Research model (SANTOS *et al.*, 2021b)



associations between five of the six user types with the gamification designs, however, we identified that there is no consistent pattern of associations. When analyzing the PLS-PM results (see Table 27), similarly to the results found by Hallifax *et al.* (HALLIFAX *et al.*, 2019b) and Tondello *et al.* (TONDELLO *et al.*, 2016), our results showed that Philanthropists did not present a significant association with any gamification design. Moreover, our results showed that Philanthropists presented a negative association with the Fictional gamification design in terms of perceived sense of accomplishment and preference, the only design that did not present the "assistant" that explained what the student would do in that gamification design. Since Philanthropists are motivated by interaction with others (TONDELLO *et al.*, 2016), we believe the lack of the "assistant" presence can be understood by Philanthropists as a lack of interaction.

Analyzing our results in comparison with other studies (TONDELLO *et al.*, 2016; TONDELLO; MORA; NACKE, 2017), we believe that Achievers had a strong significant association with the Performance and Social gamification designs in the perceived sense of accomplishment measurement, especially because these two designs showed game elements and situations that could lead the user to feeling achievement and to demonstrate competence, which intrinsically motivates this user type (TONDELLO *et al.*, 2016). We believe that when implemented in a gamified system, the Performance (game elements: Level, Point, Progression, Stats, and Acknowledgement) and Social (game elements: Social Pressure, Competition, Social Status, and Cooperation) gamification designs would probably lead the Achievers to have a feeling of advancement in their skills, and thus motivate them.

Since Players are motivated by extrinsic rewards (TONDELLO *et al.*, 2016), we believe that the significant associations with the Ecological gamification design were related to the game elements of Rarity and Economy. Orji *et al.* (ORJI; TONDELLO; NACKE, 2018) found that Players tend to be motivated by Competition and Cooperation, which can explain the positive significant association with the Social gamification design in terms of perceived sense of accomplishment. At the same time, Players presented a slight and negative significant association with the Social gamification design in terms of preference. Thus, even though the Social gamification design brought a sense of accomplishment to the Players, this gamification design was not preferred by them. Players also presented a positive significant association with the Personal gamification design, probably because the game element Puzzle (Challenge), related to this user type in other studies (TONDELLO; MORA; NACKE, 2017; TONDELLO *et al.*, 2016).

Free Spirits only presented one significant association with the Social gamification design, however, it was negative. Also, this user type was the one that presented more negative associations, since we were able to identify that Free Spirits presented negative non-significant associations with all of the gamification designs. Considering preference, this user type presented negative non-significant associations with Fictional gamification design and considering the perceived sense of accomplishment, negative non-significant associations with Personal, Performance, Ecological, and Social gamification designs. This was unexpected considering that we presented game elements in this study that were related to this user type in previous studies (*e.g.* Puzzle (TONDELLO; MORA; NACKE, 2017; TONDELLO *et al.*, 2016) and Level (TONDELLO; MORA; NACKE, 2017)).

Socialisers were the user type that presented more significant associations, including a strong significant association with the Social gamification design. The game elements presented in the Social gamification design are important to ensure interactions between the users (TODA *et al.*, 2019a) and can be related directly with the Socialisers that are intrinsically motivated by relatedness (TONDELLO *et al.*, 2019). We understand that the Social gamification design, when implemented in a gamified system, could guide the Socialisers into relatedness, which would motivate them. The game elements of the Social gamification design (game elements: Social Pressure, Competition, Social Status, and Cooperation) have already been individually associated with Socialisers in previous studies (TONDELLO *et al.*, 2016; TONDELLO; MORA; NACKE, 2017). Probably, the strong significant association with the Fictional gamification design occurred because the game element Narrative is related to the user's interaction with the system (TODA *et al.*, 2019a), and the slight significant association with the Personal gamification design because of the game element Puzzle (Challenge), that has been related with this user type before (TONDELLO *et al.*, 2016). They also presented a slight and negative significant association with the Performance gamification design, probably because of the game elements showing progress in this gamification design, considering that similar results were found by Hallifax *et al.* (HALLIFAX *et al.*, 2019b).

We believe Disruptors presented a significant association with the Social gamification design especially because of the game element Competition. Tondello *et al.* (TONDELLO *et al.*, 2016) identified that competition is a game element that can be related to this user type, and Orji *et al.* (ORJI; TONDELLO; NACKE, 2018) showed that competition would motivate people with high disruptor tendencies. Also, the Social gamification design is the one that shows interactions with other students, and Disruptors need interactions to influence other users to try to change the system (MARCZEWSKI, 2015). Hence, this can be another reason for this significant association.

Our results also presented some non-significant associations between the user types and the gamification designs that indicate some possibilities. As aforementioned, the Philanthropists presented a non-significant association with the Fictional gamification design. We believe that designers should guarantee that, especially when the gamified system does not present interactions with other users, they have at least a figure to simulate interaction (*e.g.* animated pedagogical agents or an "assistant" from the system). Considering the non-significant associations, Players presented a positive association in terms of the perceived sense of accomplishment with Performance and Personal gamification designs. Since this user type also presented a significant association with the Personal gamification design in terms of preference, we understand that the implementation of this design would be a good option to increase the motivation of this user type. The association with the Performance gamification design could be explained by the use of the game elements Level and Point, related to this user type before (TONDELLO *et al.*, 2016; TONDELLO; MORA; NACKE, 2017). Therefore, the implementation of this design for Players also could be a good option to increase the sense of accomplishment in these users. The Disruptors presented a negative association with the Ecological, Personal, and Fictional gamification designs. The Personal and Fictional designs represented how the system would work, therefore, this could be seen by the Disruptors as the boundaries of the system. The game element Time Pressure, represented by a clock in the Ecological design, could also be seen by the Disruptors as a limitation of their actions. Since they are motivated by change (TONDELLO *et al.*, 2016), we understand these designs could be understood by Disruptors as limiting, which could explain these negative associations.

Our results show that the perceived sense of accomplishment measurement has more homogeneous results than the preference measurement (see Table 26). This demonstrates that only measuring the preference for game elements might not be sufficient to understand the effects of the game elements on user experience. For instance, some user types presented a significant association with a gamification design in terms of perceived sense of accomplishment, but this not has happened in terms of preference with the same gamification design. Considering that the feeling of accomplishment drives the user to complete tasks or goals and reflects the user's engagement (HÖGBERG; HAMARI; WÄSTLUND, 2019), we believe the user types that presented a significant association with a gamification design in terms of perceived sense of accomplishment, can present better progress when using gamified systems that have that set of game elements.

When we do not consider the user types, the game elements of the Performance and Social gamification designs can be used for all users, since these two designs showed a predominance in the preference and perceived sense of accomplishment results (see Table 26). Thus, gamified systems must present the group of game elements that create interactions between the users, and the group of game elements that provide feedback to them. Our results corroborate other studies (MORA *et al.*, 2019; HALLIFAX *et al.*, 2019b; TONDELLO; MORA; NACKE, 2017) showing that users have different preferences based on their user types. Considering only preference by user type, the Social gamification design is strongly related to Socialisers and can also be used with Disruptors, while the Personal gamification design can be indicated for Players. Furthermore, the user type is a factor that affects how the users perceived their sense of accomplishment. Considering the perceived sense of accomplishment and the user types, the Social and Performance gamification designs are the most related to Achievers, and Socialisers seem to be strongly affected by the Social and Fictional gamification designs. Philanthropists seem not to be affected by the game elements represented in this study, and Free Spirits might not be positively affected by most of the game elements.

According to our results, it is possible to select the most appropriate gamification designs for each system user, according to their Hexad user type and based on two different approaches (preference and/or perceived sense of accomplishment). This can help designers to personalize gamification, and therefore positively affect the users. To personalize gamified environments for people with higher Achiever tendencies, designers should focus on implementing the game elements from the Performance and Social gamification designs, since our results indicated a significant association in terms of perceived sense of accomplishment. The game elements from the Ecological and Personal gamification designs should be avoided since they presented a negative non-significant association. For people with higher Disruptor tendencies, designers should focus on implementing the game elements from the Social gamification design, especially the game element Competition. Considering the non-significant associations this user type presented, if the gamified environment is based on the preference for game elements, it is important to avoid or use with caution the game elements from the Ecological, Personal, and Fictional gamification designs.

For people with higher Player tendencies, designers can focus on the game elements from the Personal and Ecological gamification designs. Since Players presented negative (preference) and positive (sense of accomplishment) significant associations with the Social gamification design, designers can give these users the possibility to choose if they want to interact with the game elements from this gamification design. For people with higher Socialiser tendencies, designers should focus on implementing the game elements from the Social gamification design, since this user type presented a significant association with this gamification design in both approaches (preference and sense of accomplishment). The game elements from the Personal and Fictional gamification designs can also be implemented to increase the experience for this user type. Game elements from the Performance gamification design should be avoided.

Since Free Spirits only presented a negative significant association with the Social gamification design, we indicate that the game elements from this gamification design should be avoided or used with caution. Considering the negative and non-significant associations this user type presented with the other gamification designs, we understand that designers could give users with high Free Spirit tendencies the possibility to disable the game elements or to freely choose which game element each user would interact with. The Philanthropists did not present any significant association, therefore, designers can use the non-significant associations presented in our results to personalize gamified environments to this user type or also implement the possibility to disable the game elements or to freely choose which game element each user would interact with. Furthermore, we indicate that the system should provide interaction with other users, or at least with the system itself, through an "assistant". In Table 28 we summarize these recommendations of which gamification designs can be used to personalize gamified systems based on the significant associations we found (see Table 27).

Table 28 – Recommendations to personalize gamification. (SANTOS *et al.*, 2021b)

	Preference	**Sense of Accomplishment**
Philanthropist	∅	∅
Achiever	∅	+ SPF and + SS
Player	- SS and + SP	+ SE and + SS
Free Spirit	-SS	∅
Socialiser	- SPF and + SS	+ SF, + SP and + SS
Disruptor	+ SS	∅

Key: ∅: Without significant association; +: Significant positive association; -: Significant negative association; SF: Storyboard Fictional; SP: Storyboard Personal; SPF: Storyboard Performance; SE: Storyboard Ecological; SS: Storyboard Social.

5.1.4 Limitations and opportunities identified for future studies

Some limitations have emerged during the study and they need to be considered. Although the internal reliability for the Disruptors was below the acceptable threshold, we were able to identify that for this user type, there exists a kind of predominance: all of the Disruptors, except one, presented only this user type as the dominant user type, and we were not able to find any study that has reported similar results. As another observation, the use of gamification designs can bring different results from the use of a real gamified system. Our design focused on representing the different phases a gamified system would have, thus, they were a design concept of a gamified system. While storyboards represent the "ideal" scenario to evaluate a design idea, the implementation brings other design decisions (ORJI; VASSILEVA; MANDRYK, 2014), which could influence the users' response. Also, two of the storyboards did not represent the moment the student would answer questions in the system, considering they were designed to show how a student would create a profile and also the moment that the student would know the system. Some respondents could see this as a gap, which could subsequently influence their responses to the survey.

Based on the results obtained from our study, as well as the limitations our study raised, it is possible to propose a series of new studies to deepen this research domain. Initially, our study focused on answering research questions in the field of education (*i.e.*, using storyboards representing a gamified setting). We believe that future studies should be conducted in different areas (*i.e.*, replicating our study in different domains) expanding our results by using specific gamification designs suited to the context. Besides that, almost all the respondents were older than 15 years, which can prevent the results' generalization for younger people. Future studies should focus on people under 15 years old, analyzing if age can change the preference and perceived sense of accomplishment, thus expanding our results. Since most of the respondents had reported that they play games (67%), an interesting perspective future studies can focus on is whether the gaming habit affects the preference and perceived sense of accomplishment in gamified systems.

In our study, we measured one dimension of the gameful experience (*i.e.*, Accomplishment), and according to Högberg *et al.* (HÖGBERG; HAMARI; WÄSTLUND, 2019), the dimension of Immersion also seems to reflect user's engagement. Thus, future studies can be carried out to measure this dimension and also assess the effects of the user type on other gameful experience dimensions (*e.g.*, Challenge, Competition, and Playfulness). It is also important to investigate whether the results obtained in this study are maintained in ecological environments (*i.e.*, real gamified systems). Thus, we recommend that future studies can implement the gamification designs proposed and validated in our study in gamified systems, and evaluate the effects of different versions of the system on the users' experience during the system usage. Also based on the results obtained in our study, it is possible to understand which gamification designs are more or less effective concerning the users' sense of accomplishment. This can be useful, for example, to enable gamified system designers to personalize the gamification in a way that positively affects users. To make this task easier for designers, we recommend that future research may propose recommender systems (RESNICK; VARIAN, 1997) to suggest the most suitable gamification design for each user according to their Hexad user type.

5.1.5 Summary

Overall, this study demonstrated that the user types from the Hexad model have different preferences and a sense of accomplishment over gamification designs. To avoid the use of only the game elements that are considered the most used in research, the game elements used in these designs were chosen from an empirically validated gamification taxonomy that groups twenty-one game elements into five dimensions. The results from this study also corroborated prior research in identifying that the game elements presented in the Performance (Point, Progression, Level, Stats, and Acknowledgment) gamification design can be considered most adequate for all users. Based on the study results, it was possible to create a set of recommendations on how to personalize gamified systems based on the Hexad user types, which can help designers and researchers to design personalized gamified systems.

5.2 The relationship between the Hexad user types and demographic aspects

Despite the large number of studies investigating how personalization could improve gamification, few of them focus on understanding the influence of multiple users' characteristics when defining the user profile, while the majority choose to focus on personalization strategies based on only one or a few characteristics (KLOCK *et al.*, 2020; RODRIGUES *et al.*, 2020; OLIVEIRA *et al.*, 2022b). Since users have different demographic profiles and different user types, this personalization based just on a few characteristics may only partially fit the user preferences, and thus, fail to increase their motivation (KLOCK *et al.*, 2020). Therefore, the use of multiple user aspects to define how to personalize a gamified setting could lead designers and researchers to create a more effective gamification design.

We addressed this challenge through this study with 340 participants, where we *i)* collected a set of demographic information about them (*i.e.*, age group, gender, and educational level), *ii)* collected their gaming habits (*i.e.*, if they play and the frequency), *iii)* identified their Hexad user types (Philanthropist, Achiever, Socialiser, Free Spirit, Player, and Disruptor), and then, *vi)* analyzed how their demographic and gaming habits characteristics were related to their Hexad user types. The analysis indicated that, even though the user types have presented significant associations with the demographic aspects collected, these associations were weak. The results indicate that different users' characteristics should be considered according to their user types when defining a personalization strategy, therefore, there is a necessity for different types of personalization. The results of our study can be useful for researchers and gamification designers when modeling gamified systems, indicating possible paths to personalize gamified settings (*i.e.*, based on the user type and their demographic aspects), as well as indicating possibilities for future studies in the field.

5.2.1 Method, data collection, and participants

The data used in this study was gathered from the prior research reported in section 3.1. Therefore, the data set was composed of demographic information, gaming habits, and Hexad user type. The information used in this dataset was of gender (woman, man, preferred not to answer, and other), age group (10-14 years old, 15-19 years old, 20-24 years old, 25-29 years old, 30-34 years old, 35-39 years old, 40-44 years old, 45-49 years old, 50-54 years old, 55-59 years old, and more than 60 years), educational levels (elementary school, middle school, high school, bachelor, specialized or MBA courses, M.Sc, and Ph.D.); if playing games was a habit (yes or no) and frequency of play (every day, every week, rarely, and I do not know). From the 340 participants, 172 self-reported as women, and 164 self-reported as men. Only four respondents preferred not to report their gender or answered with the option "other". The dataset was formed by people of all educational levels and age groups presented in the survey, and most of the participants reported that playing games was a habit, even though most of them reported that they rarely play. All the demographic information about the participants can be seen in Table 29.

Table 29 – Demographic information and gaming habits of the respondents (study 6)

Variable		%	Variable		%
	Women	51%		10 to 14	0,3%
Gender	Men	48%		15 to 19	9%
	Other / Preferred not to answer	1%		20 to 24	14%
				25 to 29	14%
	Elementary/Middle School	2%		30 to 34	17%
Educational Level	High School	9%	**Age**	35 to 39	12%
	Bachelor	32%		40 to 44	11%
	Specialized Courses/ MBA Courses	21%		45 to 49	10%
	M.Sc.	25%		50 to 54	6%
	PhD	11%		55 to 59	4%
				Over 60	1%
				Every day	13%
	Play games	67%	**Frequency**	Every week	21%
Gaming Habits				Rarely	47%
				I do not know	19%
	Do not play Games	33%			

5.2.2 Results

Initially, we tested the normality of the data using the Shapiro-Wilk test as recommended by (WOHLIN *et al.*, 2012), which indicated that our data followed a non-parametric distribution. Then we measured the means and standard deviation of each Hexad sub-scale (*i.e.*, the four items that are used to evaluate each Hexad user type). The results, reported in Table 30, indicated that Philanthropists and Achievers presented the higher score (*i.e.*, are the predominant user types on the sample), while Disruptors presented the lower score (*i.e.*, are the least predominant user type on the sample). This result is similar to other recent studies (TONDELLO *et al.*, 2019; ALTMEYER *et al.*, 2020b; KRATH; KORFLESCH, 2021) that used the Hexad scale to evaluate the user types of the respondents.

Then, we measured the internal reliability of each sub-scale using Cronbach's α, which is widely used in social sciences to estimate scale reliability (PETERSON; KIM, 2013). We found acceptable values ($\alpha \geq 0.70$) for all user types, except for the Disruptor, which was slightly below the acceptable. Other studies (TONDELLO *et al.*, 2019; POECZE; RONCEVIC; ZLATIC, 2019; OOGE *et al.*, 2020; KRATH; KORFLESCH, 2021) also have found $\alpha \leq 0.70$ for this user type. The Average Variance Extracted (AVE), which measures the amount of variance explained by a construct and must be higher than 0.5 (FORNELL; LARCKER, 1981), also indicated problems with the Disruptor sub-scale. We then calculated the Composite Reliability (CR), which is an option to measure reliability through structural equation modeling and is equivalent to coefficient omega (PADILLA; DIVERS, 2016). Prior literature (FORNELL; LARCKER, 1981) indicated that even when the AVE is lower than 0.5 if the CR is higher than 0.6, the convergent validity can be considered adequate. In the CR we found acceptable values (CR $\geq$ 0.70) for all user types, indicating the internal reliability of the data.

Table 30 – Descriptive and reliability analyses (study 6)

User type	**M**	**SD**	**FM**	**FSD**	**MM**	**MSD**	α	**CR**	**AVE**
Achiever	24.0	4.75	23.42	5.61	24.57	3.58	0.879	0.914	0.728
Disruptor	14.68	5.29	13.9	5.46	15.34	4.93	0.673	0.775	0.471
Free Spirit	22.55	4.59	22.25	5.30	22.79	3.69	0.754	0.838	0.568
Philanthropist	24.17	4.76	23.88	5.46	24.46	3.90	0.885	0.920	0.743
Player	20.55	5.57	19.73	5.96	21.41	4.98	0.806	0.861	0.612
Socialiser	20.46	5.69	20.46	6.02	20.62	5.02	0.880	0.913	0.726

Key: M: Mean Scores; SD: standard deviation; FM: Women Mean Scores; FSD: Standard deviation from women; MM: Men mean scores; MSD: standard deviation from men; α: Cronbach's; CR: Composite Reliability; AVE: Average Variance Extracted. Values in grey are $\alpha \leq 0.70$ and AVE ≤ 0.50

To ensure that the constructs measures were the expected by theory (*i.e.*, that the intercorrelations between the variables were not too high (KLINE, 2015)), we also measured the discriminant validity of our data. We found acceptable values, since all the square roots of the variables' AVE were larger than the correlations that the variable had with the other variables (FORNELL; LARCKER, 1981), and all of the variables presented correlations between them below 0.85. The discriminant validity can be seen in Table 31.

Table 31 – Discriminant Validity (study 6)

	Achiever	*Age*	**Disruptor**	*Education*	**Free Spirit**	*Gender*	*If they play*	**Philanthropist**	**Player**	**Socialiser**	*Frequency*
Achiever	0.853										
Age	0.070	1.000									
Disruptor	0.439	0.079	0.686								
Education	0.162	0.625	0.250	1.000							
Free Spirit	0.713	0.003	0.510	0.145	0.754						
Gender	0.116	-0.054	0.195	0.055	0.100	1.000					
If they play	0.112	-0.056	0.095	0.006	0.081	0.254	1.000				
Philanthropist	0.773	0.191	0.358	0.245	0.658	0.060	0.069	0.862			
Player	0.476	-0.123	0.358	-0.059	0.410	0.163	0.187	0.335	0.782		
Socialiser	0.547	0.182	0.258	0.138	0.465	-0.034	-0.000	0.654	0.336	0.852	
Frequency	0.085	-0.117	0.067	0.028	0.114	0.225	0.622	0.026	0.175	-0.030	1.000

Key: Words in bold are related to the user types, while words in italic are related to the demographic and gaming habits

Considering the results of the study conducted by Tondello *et al.* (TONDELLO *et al.*, 2019) that identified a partial overlap between the user types, we also measured the correlation between the user types using Kendall's τ test. We used Kendall's τ test considering that when the data follows a non-normal distribution, the correlation coefficients need to be calculated from the ranks of the data and not from the actual values (AKOGLU, 2018). Our results, which can be seen in Table 32, also indicated that the user types presented statistically significant correlations between them. After using the conversion table proposed by Gilpin (GILPIN, 1993) and comparing the results with the interpretation of the strength of Pearson's correlation coefficients (DANCEY; REIDY, 2007), it was possible to identify that most of the correlations were moderate or weak.

Table 32 – Bivariate correlation coefficients (Kendall's τ) between the user types (study 6)

User Type	Achiever	Disruptor	Free Spirit	Philanthropist	Player	Socialiser
Achiever	1.000					
Disruptor	0.195**	1.000				
Free Spirit	0.414**	0.308**	1.000			
Philanthropist	0.465**	0.103**	0.378**	1.000		
Player	0.343**	0.239**	0.312**	0.183**	1.000	
Socialiser	0.326**	0.081*	0.304**	0.472**	0.245**	1.000
Key: * $p \leq 0.05$; ** $p \leq 0.01$						

To start to answer our research question, also using Kendall's τ test after transforming the data collected into ordinal data, we measured the correlation between the Hexad user types and the demographic variables, which results can be seen in Table 33. Disruptors and Players have presented a correlation with gender; Philanthropists and Socialisers with age; Disruptors and Philanthropists with Educational Level; and Players have presented a correlation with gaming habits (if they play and frequency). Players also have presented a negative significant correlation with age. After using the conversion table proposed by Gilpin (GILPIN, 1993) and comparing the results with the interpretation of the strength of Pearson's correlation coefficients (DANCEY; REIDY, 2007), it was possible to identify that all of the significant correlations were weak.

Table 33 – Bivariate correlation coefficients (Kendall's τ) between the user types and the variables (study 6)

	Achiever	Disruptor	Free Spirit	Philanthropist	Player	Socialiser
Gender	0.030	**0.133****	-0.002	-0.034	**0.101***	-0.030
Age	0.035	0.038	-0.010	**0.181****	-0.097*	**0.111****
Educational Level	0.044	**0.127****	0.052	**0.150****	-0.055	0.061
If they play	0.068	0.063	0.030	0.003	**0.111***	-0.033
Frequency of play	0.052	0.044	0.081	-0.010	**0.107***	-0.049
Key: * $p \leq 0.05$; ** $p \leq 0.01$; The statistical significant correlations are in bold. Values in gray are statistically negative significant correlations						

Finally, inspired by other recent studies in the gamification field (ORJI; TONDELLO; NACKE, 2018; HALLIFAX *et al.*, 2019b; STUART; LAVOUÉ; SERNA, 2020), to further answer our research question we also used Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis to measure the associations between the user types, demographic information, and gaming habits. The PLS-SEM is a reliable method for estimating cause-effect relationship models with latent variables (HAIR *et al.*, 2016). A latent variable is a variable that can not be directly observed, thus, it is inferred from other variables that are observed. In Figure 6 we present the path model of our study. The path model is a diagram that shows the variables' relationships that will be estimated in the structural equation modeling analysis, where the latent variables are represented as circles or ovals and the observed variables are represented as rectangles (SARSTEDT; RINGLE; HAIR, 2017).

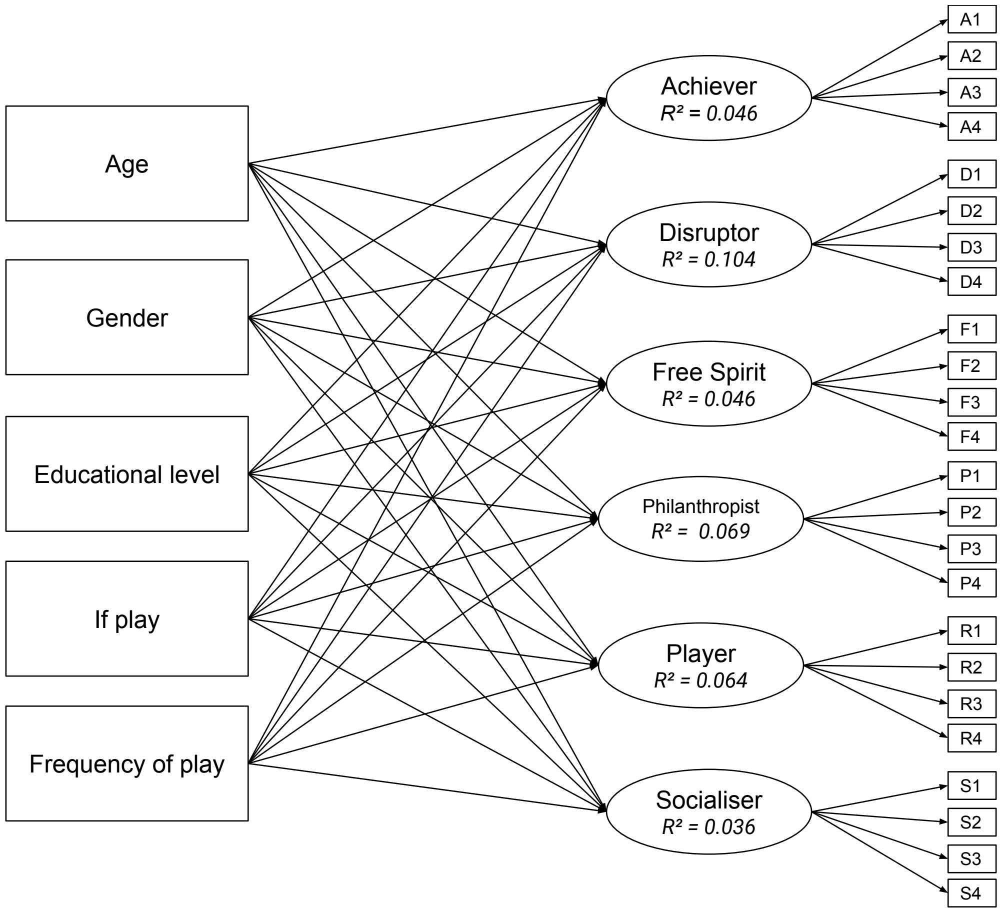


Figure 6 – Path model (study 6)

The PLS-SEM analysis also indicated significant associations between the user types and the demographic information. The results indicated that Disruptor (β = 0.306***), Free Spirit (β = 0.213***), Philanthropist (β = 0.200***), and Achiever (β = 0.175**) presented a significant association with educational level; Disruptor (β = 0.163***) and Player (β = 0.114**) presented a significant association with gender; and Socialiser presented a significant association with age (β = 0.150**). In Table 34 we present the PLS-SEM correlation matrix with all the associations. The coefficient of determination (R), which values are presented in Figure 6, measures the variance in each of the constructs and is a measure of the explanatory power of the model (HAIR *et al.*, 2019). Our results showed that the model explained 4.6% of the variance for the Achievers, 10% of the variance for the Disruptors, 4.6% of the variance for the Free Spirits, 6.9% of the variance for the Philanthropists, 6.4% of the variance for the Players, and 3.6% of the variance for the Socialisers. Thus, the R values indicated a weak predictive ability of the endogenous variables.

Table 34 – PLS-SEM associations between the user types and the demographic aspects and gaming habits (study 6)

	β	p-values	CI 2.5%	CI 97.5%
Age → Achiever	-0.030	0.705	-0.194	0.104
Age → Disruptor	-0.103	0.183	-0.245	0.061
Age → Free Spirit	-0.118	0.152	-0.272	0.031
Age → Philanthropist	0.070	0.327	-0.088	0.196
Age → Player	-0.099	0.162	-0.231	0.047
Age → Socialiser	**0.150****	0.035	0.000	0.284
Educational level → Achiever	**0.175****	0.013	0.027	0.283
Educational level → Disruptor	**0.306*****	0.000	0.170	0.415
Educational level → Free Spirit	**0.213*****	0.003	0.023	0.326
Educational level → Philanthropist	**0.200*****	0.002	0.071	0.314
Educational level → Player	-0.005	0.934	-0.124	0.133
Educational level → Socialiser	0.046	0.532	-0.109	0.172
Gender → Achiever	0.082	0.103	-0.021	0.175
Gender → Disruptor	**0.163*****	0.006	0.048	0.262
Gender → Free Spirit	0.063	0.265	-0.053	0.171
Gender → Philanthropist	0.039	0.394	-0.052	0.125
Gender → Player	**0.114****	0.049	-0.021	0.207
Gender → Socialiser	-0.030	0.608	-0.145	0.083
If they play → Achiever	0.085	0.261	-0.085	0.231
If they play → Disruptor	0.066	0.335	-0.068	0.199
If they play → Free Spirit	0.013	0.872	-0.141	0.151
If they play → Philanthropist	0.081	0.258	-0.050	0.216
If they play -→ Player	0.110	0.140	-0.027	0.252
If they play → Socialiser	0.032	0.678	-0.107	0.194
Frequency of play → Achiever	0.005	0.943	-0.131	0.144
Frequency of play → Disruptor	-0.032	0.636	-0.148	0.111
Frequency of play → Free Spirit	0.072	0.391	-0.090	0.221
Frequency of play → Philanthropist	-0.031	0.665	-0.163	0.100
Frequency of play → Player	0.070	0.350	-0.083	0.199
Frequency of play → Socialiser	-0.026	0.736	-0.176	0.118

Key: ** $p \leq 0.05$; *** $p \leq 0.01$. The statistically significant associations are in bold

5.2.3 Discussion

In this study, we focused on analyzing the relationship between Hexad user types and different demographic aspects and gaming habits. To investigate the topic, we analyzed 340 answers from people with different demographic backgrounds and gaming experiences.

Overall, the user types that are intrinsically motivated (*i.e.*, Achiever, Philanthropist, Socialiser, and Free Spirit) presented a higher score (see Table 30), which was indicated in prior research (FISCHER; HEINZ; BREITENSTEIN, 2018; TONDELLO *et al.*, 2019; OOGE *et al.*, 2020; MANZANO-LEÓN *et al.*, 2020). When analyzing the scores by gender, women's and men's scores also followed this distribution Achievers and Philanthropists as the most common user types, and Disruptors as the least common user type. Our results indicated that men scored higher than women in all the user types (see Table 30), differently from the study of Tondello *et al.* (TONDELLO *et al.*, 2019) (where women scored higher than men in all the user types derived from the intrinsic motivations), and from the study of Fischer *et al.* (FISCHER; HEINZ; BREITENSTEIN, 2018) (where women scored higher than men in all the user types derived from the intrinsic motivations except Achievers). However, our results indicated that the difference between the scores by gender in the user types derived from the intrinsic motivations was smaller than the difference between the scores by gender in the user types derived from the extrinsic motivations. In our results, the highest difference in the scores of different genders occurred in the Player user type, when men scored 1.68 points higher than women, which corroborates prior research (FISCHER; HEINZ; BREITENSTEIN, 2018; TONDELLO *et al.*, 2019; MORA *et al.*, 2019; SENOCAK; BÜYÜK; BOZKURT, 2021) that also indicated that men score higher than women in this user type. A possible explanation for this is that men are more responsive to reward strategies (OYIBO; ORJI; VASSILEVA, 2017), a motivational factor for the Player user type.

When analyzing the correlations presented between the user types in Kendall's τ test (see Table 32), even though all of them were significant, most were weak correlations, with Free Spirit - Achiever, Philanthropist - Achiever, Philanthropist - Free Spirit, Player - Achiever, and Socialiser - Philanthropist presenting moderate correlations. Other studies have also indicated correlations between the Hexad user types (TONDELLO *et al.*, 2019; LOPEZ; TUCKER, 2019; KRATH; KORFLESCH, 2021) and these correlations are expected, considering that some user types' motivations are related. Philanthropists and Socialisers are motivated by interaction with others, with Socialisers focusing on the interaction itself and Philanthropists focusing on the interaction to help other users (TONDELLO *et al.*, 2019). Players and Achievers are both motivated by achievement, with Achievers focusing on competence and Players focusing on rewards (TONDELLO *et al.*, 2019). As indicated by Tondello *et al.* (TONDELLO *et al.*, 2019), the correlation between Achievers and Free Spirits was not predicted by the theory, however, our results corroborate theirs indicating this correlation.

When we consider the correlations presented between the user types and demographic information of the respondents in Kendall's τ test (see Table 33), Disruptors presented a weak significant correlation with gender and educational level, Philanthropists and Players with gender and age, and Socialisers with age. The correlations of the Philanthropists, Players (negative correlation), and Socialisers with age corroborate prior studies (ALTMEYER; LESSEL, 2017; TONDELLO *et al.*, 2019; MORA *et al.*, 2019) that indicated that the frequency of user types derived from the intrinsic motivations increase with age, while the frequency of user types that are extrinsically motivated decrease. The correlations of the Disruptors, Players, and Philanthropists with gender also seem to corroborate prior research (TONDELLO *et al.*, 2019; MORA *et al.*, 2019) that indicated that the user type is correlated with the gender of the user. While Tondello *et al.* (TONDELLO *et al.*, 2019) indicated that women scored higher than men on the user types from intrinsic motivations, Mora *et al.* (MORA *et al.*, 2019) indicated that there was a higher percentage of Philanthropists among women and Players among men. Players were the only user type that presented a significant correlation with gaming habits. Even though we found studies that measured the gaming habits of the respondents (TONDELLO *et al.*, 2019; LOPEZ; TUCKER, 2019; POECZE; RONCEVIC; ZLATIC, 2019; ALTMEYER *et al.*, 2020a; SENOCAK; BÜYÜK; BOZKURT, 2021), almost no further discussion was found about its relationship with the user types. The study conducted by Poecze *et al.* (POECZE; RONCEVIC; ZLATIC, 2019), indicated that Players have presented a monotonic relationship with the frequency of reading gaming-related news, and the study conducted by Senocak *et al.* (SENOCAK; BÜYÜK; BOZKURT, 2021) indicated that Players have differed significantly considering the preferred game mode (multiplayer or single-player). We believe that these results and ours, indicate that the Player is a user type that presents a correlation with the gaming habits of the users.

Analyzing the associations presented in the PLS-SEM analysis, we were able to identify significant associations between the user types and the demographic information (*i.e.*, gender, age, and educational level). The educational level was the demographic aspect with more significant associations: Disruptor (β = 0.306***), Free Spirit (β = 0.213***), and Philanthropist (β = 0.200***) presented a positive significant association with $p \leq 0.01$, and Achievers (β = 0.175**) presented a positive significant association with $p \leq 0.05$. Even though education is the most researched domain in gamification (KOIVISTO; HAMARI, 2019; KLOCK *et al.*, 2020), we were not able to find any study that associated different educational levels with the Hexad user types. When we analyzed different studies that focused on evaluating gamification in the educational context, it was possible to find results indicating that students from elementary school who received more rewards from a teacher presented better average performances (SEIXAS; GOMES; FILHO, 2016), that tailoring game elements according to the user type of the students can engage them in the learning task (HALLIFAX; LAVOUÉ; SERNA, 2020), and also that some user types might be more frequent according to the faculty affiliation (FISCHER; HEINZ; BREITENSTEIN, 2018). Considering these prior results as well as that four of the six user types presented an association with educational level in our study, we understand that this user characteristic represents a significant part of the definition of the user type, and should be considered when defining user types in samples that are not homogeneous (*i.e.*, with people from different educational levels).

Regarding gender and user types, Disruptor (β = 0.163***) presented a positive significant association with $p \leq 0.01$, and Player (β = 0.114**) presented a positive significant association with $p \leq 0.05$. Also, in our study, even though women scored lower than men in all the user types, the biggest differences between the scores by gender happened in the Disruptor and Player scores (*i.e.*, the user types that are not derived from intrinsic motivations). The study conducted by Tondello *et al.* (TONDELLO *et al.*, 2019) indicated that men scored higher in the Disruptor sub-scale than women, while the study conducted by Senocak *et al.* (SENOCAK; BÜYÜK; BOZKURT, 2021) indicated that men scored higher in the Player sub-scale than women, and the study conducted by Mora *et al.* (MORA *et al.*, 2019) indicated that there was a higher percentage of Disruptors and Players among men. We understand that the association between the Players (user types that are motivated by extrinsic rewards) and men, can be explained by the study conducted by Oyibo *et al.* (OYIBO; ORJI; VASSILEVA, 2017), which results indicated that men seem to be more responsive to rewards strategies (OYIBO; ORJI; VASSILEVA, 2017). Therefore, considering our results and prior research, we believe that the association between Disruptors and Players with gender might be related to the origin of these user types, considering the relationship men present with the user types that are not derived from intrinsic motivation.

Socialiser was the only user type that presented a significant association with age ($\beta = 0.150^{**}$). This user type also presented a correlation with age in prior studies (ALTMEYER; LESSEL, 2017; TONDELLO *et al.*, 2019; MORA *et al.*, 2019). Tondello *et al.* (TONDELLO *et al.*, 2019) found out that intrinsic motivations slightly increase with age, thus, for older samples, the frequency of user types derived from the intrinsic motivations (*e.g.*, Socialisers) will be higher. Similar results were found by Altmeyer *et al.* (ALTMEYER; LESSEL, 2017), who indicated that in an older sample there is a predominance of the user types derived from intrinsic motivations, and Mora *et al.* (MORA *et al.*, 2019), who indicated that the older the user the higher the chances of them being Socialisers, Philanthropists, and Free spirits. Therefore, based on our results and prior research, we believe that age is associated with Socialisers because this tendency might increase over time.

Overall, our results indicate that the user types are related to different demographic aspects. Even though all the user types presented a significant association with some of the demographic aspects collected in the survey, all of these associations were weak. This might indicate the necessity of different types of personalization based on other aspects, such as personality traits and gender identity, or a personalization not based only on the dominant user type (*i.e.*, the highest score). The use of the dominant user type is frequent in most of the studies about gamification (HALLIFAX *et al.*, 2019b; KLOCK *et al.*, 2020), however, some studies have indicated that this approach might not be the best one, since people display characteristics of all the user types in different degrees (TONDELLO *et al.*, 2019), the dominant user type is not sufficient to identify user preferences for game elements (HALLIFAX *et al.*, 2019b), and also changes over time (YILDIRIM; ÖZDENER, 2021). Therefore, even though the user might be highly influenced by one of the user types, the personalization strategies should be implemented considering all the user scores.

5.2.4 Strategies to user modeling based on multiple user characteristics

To create user modeling strategies based on the associations found in our results, researchers and designers should consider the user type and educational level to personalize gamified settings for Achievers, Free Spirits, and Philanthropists; user type and age to personalize for Socialisers; user type and gender to personalize for Players; and user type, educational level, and gender to personalize for Disruptors. Also, when we consider the correlations presented in the study (see Table 33) the gaming habits should be considered when creating personalization strategies for Player user type, and the age should be considered when creating personalization strategies for Philanthropist and Player user types. In Table 35 we summarize these recommendations.

Table 35 – Recommendations to define strategies to personalize gamification (study 6)

	Educational Level	Age	Gender	Gaming Habits
Philanthropist	•	•		
Achiever	•			
Player		•	•	•
Free Spirit	•			
Socialiser		•		
Disruptor	•		•	

Based on prior literature, the Periodic Table of Gamification Elements proposed to the Hexad model (MARCZEWSKI, 2017), and our results, it is possible to indicate some suggestions of game elements to personalize gamification considering multiple characteristics. For women with high Player tendencies, the most indicated game elements are Badges, Points, Prizes, Leaderboards, Virtual economy, Signposting, Feedback, and Lottery, while the most indicated game elements for men with high Player tendencies are Points, Prizes, Feedback, and Leaderboards. For women with high Disruptor tendencies, the most indicated game elements are Signposting and Feedback, while the most indicated game elements for men with high Disruptor tendencies are Voting and Feedback. These suggestions on how to personalize considering gender and user types were based on the literature review conducted by Klock *et al.* (KLOCK *et al.*, 2020), the Periodic Table of Gamification Elements proposed to the Hexad model (MARCZEWSKI, 2017), and our results.

Considering age, fewer studies presented indications of game elements according to the age of the user. According to Klock *et al.* (KLOCK *et al.*, 2020), there is a scarcity of studies with suggestions of game elements for people who are less than 30 years old, and no studies with suggestions for people who are more than 30 years were found. Considering this, our suggestions regarding age are for people who are less than 30 years old. Again, the following suggestions on how to personalize considering age and user types were based on the literature review conducted by Klock *et al.* (KLOCK *et al.*, 2020), the Periodic Table of Gamification

Elements proposed to the Hexad model (MARCZEWSKI, 2017), and our results. To personalize gamification for Philanthropists considering their age, the most indicated game elements are Collection and Gifting; for Socialisers, the most indicated game elements are Competition, Guilds, Social Discovery, Social Pressure, Social Networks, and Social Status; and for Players the most indicated game elements are Badges, Lottery, Points, Prizes, and Virtual Economy.

Like age, there is a scarcity of studies with suggestions of game elements considering the educational level of the users. To create suggestions on how to personalize based on this aspect, we conducted a snowballing review in different Literature Reviews (HALLIFAX *et al.*, 2019a; KLOCK *et al.*, 2020; BAI; HEW; HUANG, 2020; RODRIGUES *et al.*, 2020; OLIVEIRA *et al.*, 2022b), selecting studies that indicated that the participants were from K-12 education or post-secondary education. Therefore, the indications here considered the study of Hallifax *et al.* (HALLIFAX; LAVOUÉ; SERNA, 2020) to propose game elements for people in high school, the studies of Tondello *et al.* (TONDELLO *et al.*, 2016) and Bovermann and Bastiaens (BOVERMANN; BASTIAENS, 2020) to create suggestions for people in post-secondary education, the Periodic Table of Gamification Elements proposed to the Hexad model (MARCZEWSKI, 2017), and our results. To make the following suggestions, we only included game elements that were indicated in the studies selected to a specific user type at the same time that was indicated for the same user type in the Periodic Table of Gamification Elements proposed to the Hexad model. To personalize gamified settings considering secondary education, designers and researchers should consider the use of Time Pressure as game element for Achievers, Free Spirits, and Disruptors. To personalize gamified settings considering post-secondary education, Care-Taking, Sharing Knowledge, and Purpose should be implemented for Philanthropists; Challenges Certificates, Quests, Levels/Progression, and Learning could be implemented for Achievers; Exploration, Easter Eggs, Unlockable, Customization, and Creativity Tools could be implemented for Free Spirits; and Innovation Platforms, Voting, and Development Tools could be implemented for Disruptors.

Regarding the indication of game elements based on gaming habits, we considered the indications of Tondello *et al.* (TONDELLO *et al.*, 2017), the Periodic Table of Gamification Elements proposed to the Hexad model (MARCZEWSKI, 2015), and our results. The study conducted by Tondello *et al.* (TONDELLO *et al.*, 2017) demonstrated the relationship that some game elements grouped in nine different components (*i.e.*, Strategic resource management, Puzzle, Artistic movement, Sports and cards, Role-playing, Virtual goods, Simulation, Action, and Progression) might have regarding different game playing styles (*i.e.*, Multiplayer, Abstract interaction, Solo play, Competitive community, and Casual play). When considering gaming habits to personalize gamified settings for people with high Player tendencies, designers and researchers should consider the use of Progress/Feedback and Strategy for people who present have Abstract Interaction playing style and high Player tendencies, while Virtual Economy can be implemented for people who present Solo playing style and high Player tendencies. In Table 36 we summarize these recommendations.

Table 36 – Recommendations of game elements (study 6)

	Philanthropist	Achiever	Player	Free Spirit	Socialiser	Disruptor
Women			Badges, Leaderboards, Prizes, Points, Virtual economy, Signposting, Feedback, Lottery			Signposting, Feedback
Men			Points, Prizes, Feedback, Leaderboards			Voting, Feedback
Education 1		Time pressure		Time pressure		Time pressure
Education 2	Care-Taking, Sharing Knowledge, Purpose	Challenges, Certificates, Quests, Learning, Levels or Progression		Exploration, Easter Eggs, Unlockable, Customization, Creativity Tools		Innovation Platforms, Voting, Development Tools
Age <30	Collection, Gifting	Badges, Lottery, Points, Prizes, Virtual Economy			Competition, Guilds, Social Discovery, Social Pressure, Social Networks, Social Status	
Gaming 1			Progress/Feedback, Strategy			
Gaming 2			Virtual Economy			

Key: Education 1 = High School; Education 2 = Post-secondary Level; Gaming 1 = Abstract Interaction playing style; Gaming 2 = Solo playing

5.2.5 Limitations and opportunities identified for future studies

Overall this study has some limitations that should be considered. Similar to other studies in the field (POECZE; RONCEVIC; ZLATIC, 2019; KRATH; KORFLESCH, 2021; GONZÁLEZ-GONZÁLEZ *et al.*, 2022), we used limited options of gender (*i.e.,* man, woman, other, and preferred not to answer). The use of the term "other" can be considered offensive to people who are already marginalized in society (SPIEL; HAIMSON; LOTTRIDGE, 2019). We understand that this limitation could lead some respondents to not properly answer the survey or leave the study without submitting responses, therefore, limiting the sample size. Also by using a binary option to collect gender, the data collected prevented us from deeply analyzing more aspects of this characteristic (KLOCK *et al.*, 2020).

Regarding the data collected, our study was able to collect a limited number of responses from participants of only one country (*i.e.,* Brazil), which might prevent the generalization of the results. Therefore, the results here presented might not be the same considering other samples. When we consider age, we had a different number of participants in each age group *e.g.*, almost 20% of the participants in an age group (30 to 34 years old) while another age group (10 to 14 years old) representing less than 1% of the sample. Thus, considering age, the groups in our sample were not equivalent and this directly impacted the results preventing us to present more indications of modeling gamified systems considering the age of the users. Also considering age, to mitigate possible typo mistakes, we followed the methodology applied in the study conducted by Poecze *et al.* (POECZE; RONCEVIC; ZLATIC, 2019) and decided to present to the respondents' options of age groups instead of allowing the participant to provide the specific age number. This decision might prevented us to collect important information about age, preventing us to present more specific and detailed considerations about the relationship between age and user types.

Considering the game habits collected, our survey only provides an exploratory overview of the relationship between gaming habits and the user types, since we did not collect information about preferred game genres, the intention of gaming, the game mode (*i.e.*, multiplayer or single-player), etc. This decision was taken considering that we aimed to collect data from people with no experience and/or interest in games. However, this also prevented us to present more insightful results about the people who had player experiences.

Based on the results and also the study's limitations, we can indicate some possibilities for future studies that could further our results and therefore, indicate more specific recommendations on how to personalize based on multiple user characteristics. In this study, we only collected data from one country, which prevented us to make comparisons between countries that are in the same region. Future studies could collect data from different countries and compare how the same user characteristics can be related to the user types, especially considering countries that are in the same region (*e.g.*, Latin America, Europe, and Asia). This type of study also could indicate how culture can impact the user types.

Our results demonstrated that the educational level presented more significant associations with the user types than the other aspects measured. Also, the study conducted by Fischer *et al.* (FISCHER; HEINZ; BREITENSTEIN, 2018) indicated that even when considering people at the same educational level, some user types are more frequent according to the faculties affiliations. We were not able to find any study that evaluated how the different educational levels can impact the user types and their preference for game elements. This is a perspective future studies could focus on, since further investigations about how different educational levels or educational areas might impact the user type, could improve the personalization of educational gamified settings.

5.2.6 Summary

In this study, we focused on understanding more about how the Hexad user types are related to demographic and gaming aspects. The correlations and associations presented in our results indicated that some user types are more influenced by demographic aspects and gaming habits than others. The player user type was the one that presented more correlations and associations (presenting correlations/associations with age, gender, and gaming habits), while Socialiser was the user type that only presented one association (with age). All the user types presented at least one correlation or association with the demographics and gaming habits measured in the study, however, since these correlations and associations were weak or moderate, our results highlight the necessity of a further investigation into how to personalize gamified settings based on other aspects than the dominant user types and demographic characteristics.

5.3 Chapter conclusion

This chapter presented two studies that were conducted to demonstrate how the Hexad user types are related to the preference and sense of accomplishment for gamification designs, as well as other user characteristics and gaming habits. The results corroborated prior research when identifying that the preference over game elements can be different according to the profile of the user, and also that user types from the Hexad model are related to demographic and gaming aspects of the users. Moreover, both sets of recommendations on how to personalize gamified systems based on the Hexad user types that were indicated in the studies can guide designers and researchers in the design of personalized gamified systems.

CHAPTER

6

CONCLUDING REMARKS

This dissertation focused on furthering the knowledge about the changes in user profiles in gamified systems when considering the Hexad model. To do so, we aimed to answer the following research questions:

- RQ1: How do the user types changes after the first user type evaluation?
- RQ2: How to model user profiles based on the user type changes?

Over the study, six studies were conducted where we provided some answers to these questions by answering other sub-questions of the subject. To answer the first research question, we conducted the studies reported in section 3.1, section 3.2, and section 4.1, while to answer the second research question, we conducted the studies reported in section 4.2, section 5.1, and section 5.2. In this section, we present the overall contributions of this project, the limitations, and the research agenda, as well as summarize the scientific productions this project has provided.

6.1 Overall contributions

In this project, we faced the challenge of understanding how user types change over time and their influence on gamified systems. To do so, we conducted a series of studies that sought to answer different questions on the topic and generated six scientific publications. During the research, we focused on three main subtopics: *i)* the Brazilian version of the Hexad scale; *ii)* the changes user types can present over time; and *iii)* the influence of the user types in gamification design. Regarding the first subtopic, our results indicated that the current Brazilian Portuguese version of the Hexad scale can measure most of the user types, however, some items should be reviewed. Our study was the first study that analyzed the Brazilian Portuguese version of the Hexad scale, which enables its use in a country with more than 200 million native Brazilian Portuguese speakers. Moreover, our study was one of the first to analyze the Hexad scale considering a sample entirely composed of adolescents. The two studies presented in Chapter 3 advanced the state of the art by indicating that the Brazilian version of the Hexad scale can be used regardless of gender; that the items from the Disruptor sub-scale should be improved; and at the same time provided a baseline for other studies on how to create new versions of the scale to other countries that have Portuguese as the official language.

About the second subtopic, to the best of our knowledge, our research was the first to evaluate whether the Hexad user types would change over time. Moreover, our study was the first that tried to provide further analysis of how the changes in user profiles may occur. Therefore, the studies presented in Chapter 4 indicated to researchers and designers that the static personalization made in gamified systems would not be sufficient to improve user's experience, and consequently, affect user's behavior. Consequently, the main result of these studies for developers and researchers was that personalization should be dynamic. We also indicated that these results implied that the community of personalized gamification should start working on how to evaluate the user types automatically.

Finally, about the last topic, we conducted two different studies to analyze how user types could influence user preferences for gamification designs. The results of the studies presented in Chapter 5 indicated that the user types from the Hexad model influence the preference and sense of accomplishment for gamification designs and that only measuring preference might not be enough to create a personalized environment for users. We also analyzed how user types from the Hexad model could be related to other user characteristics when considering the user profile. Our results indicated that different user types are related to different user aspects and gaming habits, and therefore, we could model different profiles for the users in gamified systems. Moreover, based on results from the studies about the relationship between user types, gamification designs, and other user aspects, we indicated to researchers and designers sets of recommendations on how to personalize gamified systems.

6.2 Limitations and opportunities identified for future studies

As mentioned in previous chapters, the studies here reported presented several limitations that impact the results. Overall, even though we have conducted different data collections, we focused on collecting data only from Brazilian respondents. This decision, which was made considering the necessity of evaluation of the Hexad Scale in Brazilian Portuguese (see Chapter 3), might have a direct impact on the results, *i.e.* preventing its generalization. Also, we were not able to collect a dataset large enough to conduct other types of analyses (*e.g.*, using machine learning). This prevented us for example to work on the prediction of the user type changes.

Besides the specific research agendas reported in previous chapters, there are other studies that can be conducted to further the results here presented. Our research about the Hexad scale (see Chapter 3) indicated that some items should be reviewed. Considering this result and other recent studies about the scale (KRATH *et al.*, 2023), short versions might be an option for the items that presented problems in this and other studies. However, we understand that improvements seemed to be necessary for better measurement of the Hexad user types. Therefore, more than short versions or new translations, new items might be necessary to properly measure the Hexad user types, especially the Disruptor profile.

Gamification is a recent field and consequently, some research topics in the area are still little explored. While our prior research (see section 4.1) and the study conducted by Yildirim and Ozdener (YILDIRIM; ÖZDENER, 2021) have focused on *whether* the user type change, in the study presented on section 4.2 we focused on *how* these changes happen. Future studies should move towards this type of knowledge by focusing on *why* the user types change. There are several possibilities that can be analyzed in this type of study, for example, the influence of context, gamification design, culture, or socioeconomic aspects in the changes. This would benefit researchers and practitioners by indicating possible reasons and ways to avoid or delay the changes.

6.3 Scientific production

In the following subsections, it is presented the scientific production generated during this research.

6.3.1 Papers published as first author

- Santos, A. C. G., Oliveira, W., Hamari, J., & Isotani, S. (2021). Do people's user types change over time? An exploratory study. In: CEUR-WS. Proceedings of the 5th International GamiFIN Conference, GamiFIN 2021. 2021. p. 90–99.

- Santos, A. C. G., Oliveira, W., Hamari, J., Rodrigues, L., Toda, A. M., Palomino, P. T., & Isotani, S. (2021). The relationship between user types and gamification designs. User modeling and user-adapted interaction, 31(5), 907-940.

- Santos, A. C. G., Oliveira, W., Altmeyer, M., Hamari, J., & Isotani, S. (2022). Psychometric investigation of the gamification Hexad user types scale in Brazilian Portuguese. Scientific Reports, 12(1), 4920.

6.3.2 Papers published as co-author

- Vasconcelos, G., Oliveira, W., Santos, A. C. G., & Hamari, J. (2022). ReGammend: A method for personalized recommendation of gamification designs. In: CEUR-WS. Proceedings of the 6th International GamiFIN Conference, GamiFIN 2022. 2022. p. 85–94.

6.3.3 Papers under review

- Santos, A. C. G., Muramatsu, P. K., Oliveira, W., Joaquim, S., Hamari, J., & Isotani, S. Psychometric investigation of the gamification Hexad user types scale with Brazilian Portuguese Adolescents Speakers. In review at Scientific Reports (Nature).

- Santos, A. C. G., Oliveira, W., Vassileva, J., & Isotani, S. The relationship between gamification user types and demographic aspects. In review at User modeling and user-adapted interaction (Springer).

- Santos, A. C. G., Oliveira, W., Hamari, J., Joaquim, S., & Isotani, S. You Don't Look Different, but You Have Changed: Modeling the Rank-Order Consistency of Gamification User Types Over Time. In review at the Annual Symposium on Computer-Human Interaction in Play (CHI PLAY).

6.3.4 Other scientific publications

- Santos, A. C. G., do Nascimento, I. M., & Oliveira, W. (2023, April). Da BNCC à BNCC Computação: Histórico, Afinidades e Desafios na Implementação de um Currículo Único. In Anais Estendidos do III Simpósio Brasileiro de Educação em Computação (pp. 52-53). SBC.

- do Nascimento, I. M., Santos, A. C. G., & Oliveira, W. (2023, April). Como Enfrentar o Desengajamento dos Estudantes de Computação da Educação Básica Utilizando Gamificação?. In Anais Estendidos do III Simpósio Brasileiro de Educação em Computação (pp. 50-51). SBC.

6.4 Research Internship and Scientific Community Participation

During the second semester of 2022, I had a research internship at the University of Saskatchewan (Canada), under the supervision of Prof. Dr. Julita Vassileva. This internship was approved by the University of São Paulo and the University of Saskatchewan and was funded by the Emerging Leaders in the Americas Program (ELAP). During the internship, I was Visiting Research Student at the University of Saskatchewan, where I developed the study reported on section 5.2, gave lectures about gamification to undergraduate and graduated classes, and also made a presentation about gamification to the Multi-User Adaptive Distributed Mobile And Ubiquitous Computing (MADMUC) Lab.

Over the master's, I also developed other activities for the academic community, acting as a reviewer of the Hawaii International Conference on System Sciences (HICSS) in 2022 and 2023; the ACM SIGCHI Annual Symposium on Computer-Human Interaction in Play (Chi-Play) in 2021 and 2022; and the ACM Conference On User Modeling, Adaptation, and Personalization (UMAP) in 2023.

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APPENDIX

A

EXPLORATORY ANALYSIS ON HOW USER TYPES CHANGE

Do people's user types change over time? An exploratory study

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Abstract

In recent years, different studies have proposed and validated user models (*e.g.*, Bartle, BrainHex, and Hexad) to represent the different user profiles in games and gamified settings. However, the results of applying these user models in practice (*e.g.*, to personalize gamified systems) are still contradictory. One of the hypotheses for these results is that the user types can change over time (*i.e.*, user types are dynamic). To start to understand whether user types can change over time, we conducted an exploratory study analyzing data from 74 participants to identify if their user type (Achiever, Philanthropist, Socialiser, Free Spirit, Player, and Disruptor) had changed over time (six months). The results indicate that there is a change in the dominant user type of the participants, as well as the average scores in the Hexad sub-scales. These results imply that all the scores should be considered when defining the Hexad's user type and that the user types are dynamic. Our results contribute with practical implications, indicating that the personalization currently made (generally static) may be insufficient to improve the users' experience, requiring user types to be analyzed continuously and personalization to be done dynamically.

Keywords

User modeling, User types, Gamified settings, Personalization, Hexad

1. Introduction

In the last decades, video games have become an important part of people's life and culture [1, 2, 3] and the positive experience people have playing games can affect positively their behavior [2, 3]. To evoke similar positive game experiences, gamification[1] has been used in different contexts including education [5, 6], public administration [7, 8], and health [9, 10]. Thus, one of the main goals of gamification is to change people's behavior towards a positive performance in general activities [11, 12], making the analysis of the users' experience in gamified settings one of the main concerns of researchers in recent years [9, 13, 12]. Therefore, several studies have been conducted to analyze the individual experiences of the participants in gamified settings [14, 15, 16]. Studies that emphasize users' experience focus on proposing user models according to the individualities of each person [17, 18, 19] or personalizing the systems according to these user models [20, 21, 22].

For many years, research has indicated that people have different opinions and perceptions about everyday things [23, 24, 25]. The same occurs concerning games and gamification, with several studies indicating that people have different preferences and perceptions about gamification design [10, 26, 22]. Thus, different user models have been proposed to be validated not only for games [17, 27, 18] but also for the gamification's field [19]. Despite the growing number of researches about the personalizing of gamified environments [28, 29], the results are still contradictory, and not always, the user models are faithful to each person's preferences, as well as, not always, personalization has positive effects on the users' experience [28]. Some recent studies about personalized gamification also considered personality traits to define the preference for gamification designs [30]. Studies about the stability of personality traits have been conducted to investigate how stable the personality can be over time [31, 32, 33, 34], and some of their results showed that some personality traits can be more stable over the years or according to the gender [32]. The studies about personality traits have an impact on the studies about models proposed to define players and user types since the personality traits are related to the player type itself [19, 35].

Theoretical studies argue that one of the reasons for the contradictory results in the researches about the personalizing of gamified environments is that users' preferences may change over time [36, 28], and thus, user models would need to be dynamic, as well as the personalization of systems [22]. However, in general, studies on this field are theoretical and few empirical studies have been carried out until today [28, 36], not allow-

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[1] In this study defined as "the use of game elements in non-context games" [4].

ing to know if the user types change over time in the gamification context. To start to face the challenge of understating better the user types in gamified settings, in this study, we aim to **identify if people's user types change over time**, thus answering the question "Does people's user types (Achiever, Philanthropist, Socialiser, Free Spirit, Player, and Disruptor) change over time (six months)?".

To achieve our aim, we conducted an exploratory study with 74 participants where we compared the user types of participants in the first phase with the user types of the same participants in the second phase (six months after). The main results indicate that most of the participants presented different dominant user types (*i.e.*, the strongest tendency of the participants) and also the scores of both phases presented differences. Thus, the obtained results showed that the user types can not be considered stable after six months.

The results obtained have theoretical and practical implications in the design of gamified environments, indicating that the user types of participants possibly change over time. Therefore it is not enough to analyze the participant's user types once, as well as that the static personalization of the gamification might not be enough to provide a good experience for users, being necessary to invest in approaches to provide dynamic personalization, *i.e.*, that changes according to the changing profile of users.

2. Background

This section presents the study background (*i.e.*, player and user types), as well, the related works.

2.1. Player and user types

Several studies have proposed how users can be disposed of into different player/user types according to their behavior or motivations [17, 18, 27, 37]. The player typology became an important part of studies about gamification design [28] since it helped researchers to understand more how the player/user type can affect the use of gamified systems [19, 30, 15]. The typology model proposed by Bartle [17] was one of the first and most used player type models [38, 19], which classifies the users into four different players: Achievers, Explorers, Killers, and Socializers. This player type model was based on the characteristics of players from multi-user dungeons (MUDs).

Inspired by Bartle's player type model, Yee [27] created an empirical model for player motivations with data collected from Massive Multiplayer Online Role-Playing Games (MMORPGs). Yee [27] identified ten subcomponents categorized into three main components: *i)* Achievement (advancement; mechanics and competition); *ii)* Social (socializing, relationship, and teamwork), and *iii)* Immersion (discovery, role-playing, customization, and escapism). More recently, based on neurobiological findings and data collected from players of different games, Nacke *et al.* [18] created the BrainHex with seven archetypes of players (Achiever, Survivor, Conqueror, Mastermind, Seeker, Daredevil, and Socialiser).

Ultimately, Marczewski [37] proposed the Gamification User Types Hexad [37] that classifies the users of gamified environments into six different user types, according to their motivations. This model is the first created specifically for gamification and it was based on the self-determination theory (SDT), which classifies motivation in intrinsic or extrinsic [39]. The user types of the Hexad classified according to intrinsic motivations are the Achiever (motivated by mastery); Philanthropist (motivated by purpose); Socialiser (motivated by relatedness); and Free Spirit (motivated by autonomy) [37, 40, 38]. Player (motivated by rewards) is the user type classified according to extrinsic motivations and the Disruptor (motivated by change) is a user type derived from user behavior observation in online systems [37, 40, 38, 41]. People show a stronger tendency (*i.e.*, dominant user type) for one of the Hexad user types, and yet they are also motivated by all the other user types in a certain degree [19]. Thus, the Hexad model presents the user type as a collection of six scores [19].

The Hexad have been chosen for this study, considering that is a validated user typology for gamification and have been used in a considerable number of studies about gamification in the last years [10, 14, 42, 16, 30].

2.2. Related works

Recently several studies have been conducted to understand more how the user types could be used in the gamification domain, especially in the context of personalization based on the user type choices. We defined our related works based on the results of different secondary studies on gamification, user types, and personalization [13, 28, 12], as well as, based on a snowballing review. Hallifax *et al.* [30] conducted a study with 300 participants seeking to identify which player typology would be the most suitable for tailored gamification and the motivational impact of game elements. Considering only the research about user typology, they sought to answer if the dominant user type is sufficient to discriminate users' preferences and which typology should be chosen for tailored gamification, considering the BrainHex player typology [43], Gamification User Types Hexad [37] and Big Five Factors [44]. Although they have done important findings about user typology (*e.g.*, Hexad is the most appropriate user typology for tailoring gamification [30]), they did not conduct any research to identify if there were changes in participants' user type over time.

Lopez *et al.* [42] conducted a study with 30 participants to explore the effects of the user type on the users' performance in a gamified application. To access the user type of the participants, they used the Gamification User Types Hexad [37] and the environment chosen to conduct the study was an application that promotes physical activity. Their findings (*e.g.*, the indication that user type is related to the users' performance) showed the importance of accessing the user type to increase the chances of success of an environment, however, they did not conduct another study to know if the users' type had changed over time, and consequently if their performance were the same.

Tondello *et al.* [19] conducted three large studies (n1=556, n2=1328, n3=152) to validate the scale in English and Spanish of the Gamification User Types Hexad. Their results made possible the validity of the scale in both languages, they correlated some user types (*e.g.*, there is a strong correlation between the Philanthropist and Socialiser user types) and also correlated user types with gender and age (*e.g.*, women were related with the user types with intrinsic motivations). Although the participants of the third study were the same as those in the second study, they did not analyze if the user types were the same, even though it passed six months between the studies.

Altmeyer *et al.* [45] conducted a study with 147 participants to analyze the potential of two gameful applications to predict the Hexad user types. In one application, the respondents were asked to select one statement and then they received gameful feedback. On the other, participants first experienced game elements and then decided with which they wanted to interact. Their findings (*e.g.*, participants mostly interacted with game elements that have been related to their user types in other studies) advance the literature showing that might the access of the user type can occur without the use of questionnaires, but they did not consider if the user types would change over time.

Busch *et al.* [36] conducted two online studies, (n1=592 and n2=243), about the BrainHex Model [18] in the game context. They tried to confirm the validity of the scale and if the respondents' player type were the same after six months. They did confirm that the player type of the respondents was not stable, but they used a game based player typology (BrainHex Model), which may prevent the results to be the same in the context of gamification, and did not present any demographic information that could influence the changing of the player type. Thus, as far as we know, our study is the first study conducted to identify if the user types can change over time, using a validated user type framework to the gamification context. Table 1 presents a comparison between the related works.

3. Data and methods

The study was organized in two different phases (two interventions), the first one was conducted in March/April 2020, and the second in October 2020. The first phase was divided into: *i)* survey design; *ii)* pilot study; *iii)* survey application; and *iv)* data analysis. In the second phase, we replicated the survey with the same participants and re-analyzed the data. Figure 1 summarizes the study design.

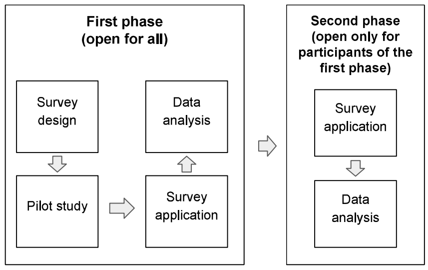

Figure 1: Study design

3.1. Materials

In both phases of this study, the questionnaire consisted of 32 questions divided into two different sections. The first one, inspired by previous studies [43, 19, 15], was used to collect the participants' demographic information and gaming habits. In this section, the participants could leave their e-mails for future studies, however, this question was not an obligatory question. The second section was used to collect the user type of the participants, using the Hexad scale proposed by Tondello *et al.* [38], which consists of 24 questions, evaluated by the respondents in a 7-point Likert Scale [46], and randomly arranged in the questionnaire, preventing the respondents to identify the questions that were similar and compose the user type characteristics, as recommended by Tondello *et al.* [38].

To improve the survey reliability, inspired in other recent studies [10, 30, 15, 41] we also inserted an "attention check question"[2]. The main objective of this question was to guarantee that the respondents were paying attention while answering the questionnaire. All the answers that did not check the right option in the "attention check question" were eliminated before the data analysis.

[2] "I like to be with my friends, but this question is just to evaluate your attention: please check option 3 to let us know that you are paying attention."

Table 1
Related works comparison

Authors	Year	Player/User Typology	AUP	AUS
Hallifax *et al.* [30]	2019	BrainHex and Hexad	•	
Lopez *et al.* [42]	2019	Hexad	•	
Tondello *et al.* [19]	2019	Hexad	•	
Altmeyer *et al.* [45]	2020	Hexad	•	
Busch *et al.* [36]	2016	BrainHex	•	•
Our study	2020	Hexad	•	•

Key: AUP: Accessed the user type of the participants; AUS: Analyzed if the player/user type is stable over time.

After the construction of the questionnaire in the first study, as recommended by Connelly [47], we conducted a pilot study. Our pilot study was conducted with ten respondents, that analyzed if the size of the questionnaire was appropriate. Eight respondents answered that the questionnaire wasn't large, then any question was taken away from it. To perform the statistical analysis we used the software SPSS (Statistical Package for the Social Sciences) 26.

3.2. Participants

For the first phase, the questionnaire was released on March 26th, 2020, was opened for thirty-eight days, and was spread by social networks (Facebook, Twitter, and Instagram) and e-mail (public lists from universities). Were collected 366 answers, of which 331 were valid according to the attention-check question. From these 331 answers, 182 respondents provided a valid e-mail and authorized the contact for other studies. These 182 e-mails were provided by 90 people that self-reported as women (49%) and 92 people that self-reported as men (51%). 71% of the respondents reported that playing games were a habit. 56% of the respondents presented only one of the six Hexad's user types (Achiever, Philanthropist, Socialiser, Disruptor, Free Spirit, and Player) as dominant user type, while the other 44% presented twenty-two different combinations of the six Hexad's user types as dominant user type (*e.g.*, Achiever and Philanthropist, Philanthropist and Socialiser).

The questionnaire of the second phase was released on October 7th, 2020, was opened for twenty-five days, and was sent to all the 182 respondents that left a valid e-mail in the first phase. Were collected 87 answers, of which 74 were valid according to the attention-check question. In this phase, 57% of the respondents presented only one of the six Hexad's user types (Achiever, Philanthropist, Socialiser, Disruptor, Free Spirit, and Player) as dominant user type, while the other 43% presented twenty-two different combinations of the six Hexad's user types as dominant user type (*e.g.*, Achiever and Philanthropist, Philanthropist and Socialiser). Table 2 presents the demographic information and gaming habits of the respondents that participated in both phases of the study.

To access the dominant user type of the participants in both phases, we measured all the scores that each participant presented in each sub-scale (*i.e.*, the four questions of each Hexad user type) and calculated where they presented the higher average score (*e.g.*, if the respondent presented as score **28 in the Achiever sub-scale**; 21 in the Philanthropist sub-scale; 20 in the Socialiser sub-scale; 18 in the Player sub-scale; 16 in the Free Spirit sub-scale; and 15 in the Disruptor sub-scale, his/her dominant user type is the Achiever). This way to calculate the dominant user type has been used similarly before [30, 35]. Instead of grouping the respondents only in the six Hexad user types, following the original Hexad results [48], the respondents that presented the higher average score repeated in more than one sub-scale were grouped into the combination of all the users they presented as the dominant user type (*e.g.*, if the respondent presented as score **28 in the Achiever sub-scale; 28 in the Player sub-scale**; 20 in the Philanthropist sub-scale; 20 in the Socialiser sub-scale; 16 in Free Spirit sub-scale; and 15 in Disruptor sub-scale, his/her dominant user type is the Achiever and Player).

The participation in the pilot study and both research phases was voluntary, thus, was not offered to the respondents any remuneration or gifts. Since the size of the questionnaire and the quality of the answers was a concern before the data collection, we understand that, as volunteers, respondents are more willing to pay attention when answering the questionnaire. Tondello and Nacke [49] also presume that volunteers participate in studies without pressure to maximize time usage, which can provide more quality of the answers.

Considering the type of this study, the sample size of both phases is adequate, according to Bentler and Chih-Ping [50] and Hair *et al.* [51], which define the necessity of at least five participants for each construct measured. Construct is a latent concept that can be defined in conceptual terms but cannot be directly measured [51] (*e.g.*, extroversion, autonomy), thus its measurement occurs indirectly through other variables.

Table 2
Demographic information and gaming habits of the participants of both phases

Demographic information					
Gender	Female	55%	Age	15-19	5%
	Male	45%		20-24	12%
Education level				25-29	16%
	Basic Education	4%		30-34	14%
	Bachelor	27%		35-39	14%
	Specialized courses	27%		40-44	18%
	M.Sc.	26%		45-49	11%
	PhD	9%		50-54	5%
	PostDoc	7%		55-59	4%
				Over 60	1%
Gaming habits					
Play games		72%	Do not play games		28%
Frequency	Everyday	14%			
	Every week	16%			
	Rarely	54%			
	I do not know	16%			

4. Results

Initially, to ensure the instrument validation for the study, we measured the internal reliability for each Hexad user type in both phases of the research. Overall, the reliability was acceptable ($\alpha \geq 0.70$, RHO A ≥ 0.70, CR ≥ 0.70, AVE ≥ 0.50) for all user types, except for the user type Disruptor (in both phases) and Free Spirit (first phase), which were slightly below the acceptable. Cronbach's values under 0.7 for the Disruptor and Free Spirit scales were also found in other recent studies [19, 41]. The reliability results can be seen in Table 3.

Table 3
Reliability results

Construct	α	RHO	CR	AVE
Achiever1	**0.863**	**0.924**	**0.874**	**0.642**
Achiever2	**0.845**	**1.148**	**0.883**	**0.655**
Disruptor1	0.648	0.668	**0.790**	0.486
Disruptor2	0.660	0.691	**0.794**	0.494
Free Spirit1	0.676	**0.987**	**0.758**	0.451
Free Spirit2	**0.785**	**0.813**	**0.853**	**0.593**
Philanthropist1	**0.873**	**0.987**	**0.909**	**0.716**
Philanthropist2	**0.890**	**0.914**	**0.924**	**0.754**
Player1	**0.743**	**0.813**	**0.830**	**0.552**
Player2	**0.851**	**0.855**	**0.900**	**0.694**
Socialiser1	**0.862**	**0.987**	**0.903**	**0.702**
Socialiser2	**0.883**	**0.893**	**0.919**	**0.740**

Key: α: Cronbach's; RHO: Jöreskog's rho; CR: Composite Reliability; AVE: Average Variance Extracted; 1: results of the first research phase; 2: results of the second research phase; Values in grey are $\alpha < 0.70$, RHO A < 0.70, CR < 0.70, AVE < 0.50

Analyzing the dominant user types it was possible to discover that 57 people (76% of the participants) presented a change of the dominant user type after six months. Once more, we considered as dominant user type the six Hexad user types and the combination between them that the respondents presented as the higher average score. The 74 participants presented, in the first phase of the study, 19 different user types combinations as dominant user type, with 51% presenting a combination of more than one user type as the strongest tendency. In the second phase, the 74 participants presented 20 different user types, with 43% presenting a combination of more than one user type. Females (78%) changed the strongest tendency more than males (73%), as well as people who play (77%) changed more than people who do not play (71%). People with a master's degree (32%) were those who more changed the dominant user type in the educational level group. Considering only the age, six of the ten age groups measured in this research, presented a change of more than 75% (15-19 years - 100%; 20-24 years - 89%; 25-29 years - 92%; 30-34 years - 80%; 40-44 years - 92%; 50-54 years - 75%).

Table 4 presents the different combinations that the 74 respondents presented as dominant user types in both phases of the study. To measure if there was a consensus between the dominant user types of both phases, we used the Kappa coefficient that is used to measure the reliability between pairwise agreement [52]. The Kappa results vary from -1 to +1 [52], where κ<0.00 the agreement is considered poor; when κ is between 0.00-0.020 the agreement is considered slight; when κ is between 0.21-0.040 the agreement is considered fair; when κ is between 0.41-0.060 the agreement is considered moderate; when κ is between 0.61-0.080 the agreement is considered substantial; and when κ is between 0.81-1 the agreement is considered almost perfect [53]. Our result (κ = 0,00) indicates that there was a very low agreement between the first and second research phases, which confirms that most of the dominant user types have changed between the research phases.

Table 4
Dominant user type

User type	1st	2nd
Philanthropist	24%	23%
Achiever	12%	16%
Free Spirit	5%	8%
Socialiser	3%	3%
Disruptor	3%	3%
Player	1%	4%
Achiever/Philanthropist	20%	8%
Achiever/Free Spirit/Philanthropist/Player/Socialiser	4%	-
Achiever/Free Spirit/Philanthropist	4%	4%
Free Spirit/Player	4%	3%
Philanthropist/Player	4%	3%
Achiever/Player	3%	1%
Achiever/Philanthropist/Player/Socialiser	3%	3%
Achiever/Socialiser	3%	3%
Achiever/Philanthropist/Socialiser	1%	1%
Philanthropist/Socialiser	1%	5%
Achiever/Free Spirit/Philanthropist/Player	1%	3%
Achiever/Free Spirit	1%	5%
Free Spirit/Philanthropist/Player/Socialiser	1%	-
Achiever/Player/Socialiser	-	1%
Free Spirit/Philanthropist/Socialiser	-	1%
Player/Socialiser	-	1%

Key: 1st: First research phase; 2nd: Second research phase.

Then, we calculated the average score for each user type in the research. Since each Hexad sub-scale is formed by four questions arranged in a 7-point Likert Scale, the maximum value a Hexad sub-scale can be is 28. Similar to other studies that accessed the user type through the Hexad scale [38, 19, 45], the Philanthropists and Achievers presented the higher average score while the Disruptors presented the lower average score. After testing the normality of the data using the Shapiro-Wilk test, we measured the bivariate correlation coefficients using Kendall's τ, since the user type scores were non-parametric. Considering the conversion table proposed by Gilpin [54], the Achievers' scores between the research phases presented a weak correlation while Socialisers', Free Spirits', Philanthropists', Disruptors', and Players' scores presented a moderate correlation.

Table 5 reports the average scores, the standard deviation, and the bivariate correlation coefficients (Kendall's τ). These results indicate that, besides the differences in the dominant user types, the six Hexad sub-scales also presented differences in the average scores in both phases.

Table 5
Mean scores, standard deviation, and bivariate correlation coefficients (Kendall's τ)

User Types	Mean score	S.D.	τ
Achiever1	24,69	4,03	0,265**
Achiever2	23,39	4,72	
Disruptor1	15,72	5,27	0,434**
Disruptor2	15,07	5,33	
Free Spirit1	23,42	3,98	0,365**
Free Spirit2	22,43	4,83	
Philanthropist1	24,92	4,07	0,379**
Philanthropist2	24,22	4,43	
Player1	21,18	4,99	0,478**
Player2	21,03	5,59	
Socialiser1	20,88	5,44	0,358**
Socialiser2	21,16	5,44	

Key: τ: Kendall's tau; 1: results of the first research phase; 2: results of the second research phase; ** p<0.01; P: Philanthropist; A: Achiever; R: Player; F: Free Spirit; S: Socialiser; D: Disruptor.

4.1. Discussion

This study examined if the Hexad's user types of 74 participants presented differences after six months. We analyzed the differences among the dominant user types and also the differences presented in the scores of the six Hexad sub-scales. Overall, our findings indicated that most of the participants presented changes in their dominant user types, and also the six Hexad sub-scales presented differences in the average scores after six months.

When we consider only the dominant user type (*i.e.*, the strongest tendency), 76% of the participants presented a change in the score. As showed in Table 4, some dominant user types have presented a considerable change between the research phases (*e.g.*, Achiever/Philanthropists were 20% of the participants of the first research phase and decreased to 8% in the second). Also is notable that in both phases, all the participants of some dominant user types have changed (*e.g.*, Achiever/Player/Socialiser did not appear in the first research phase; Free Spirit/Philanthropist/Player/Socialiser appeared only in the first research phase). These results can be related to the results found by Busch *et al.* [36], which indicated that, in the game context, some player types can be less stable over time. Our results indicate that **users present changes in the dominant user type (*i.e.*, the strongest tendency) over time, and consequently, the dominant user types can not be considered stable.**

Our results also indicate that even when we consider only the dominant user type, users can present more than one of the basic Hexad user types (*i.e.*, Achiever, Philanthropist, Socialiser, Free Spirit, Player, and Disruptor) as the dominant user type. As can be seen in Table 4, in the first research phase there were more participants disposed in more than one user type (*i.e.*, Achiever/Philanthropist = 20%) than participants disposed in some of the basic Hexad user types (*i.e.*, Achiever = 12%, Free Spirit = 5%, Socialiser = 3%, Disruptor = 3%, and Player =

1%). As indicated by previous studies [38, 19], some user types seem to be correlated, which might explain why some respondents presented more than one user type as the dominant user type. Since the user performance can be affected by the user type [42], we believe that, when considering only the dominant user type, **it is necessary to analyze if the user presents more than one user type as the dominant**.

Considering the demographic information of the respondents that changed the dominant user type, women seem to be slightly more susceptible to change the dominant user type than men (see section 4). The study conducted by Tondello *et al.* [19] showed that women scored higher in the intrinsically motivated user types (*i.e.*, Achiever, Philanthropist, Socialiser, and Free Spirit), and since our results showed that the user types Achiever, Philanthropist, and Free Spirit presented the higher difference in the average scores of both research phases, we believe that **women might be more susceptible to change the user type than men because they are more motivated by the intrinsically motivated user types.** From the descriptive analysis, it was not possible to identify how age can influence the user types' change, since the changes varied in the age groups measured in this study (see section 4). Despite that, **our results demonstrate that people can change their user types in different life stages**, showing that to personalize gamification it is important to consider other characteristics besides the user type and age group of the users.

Even though the results about the differences presented between the user types in both research phases (see Table 5) can be considered small (all the user types presented less than 1.3 points of difference in the average scores, from 28 available), we understand that, when we consider all the average scores of the user types, the participants' changes might have produced an offsetting change. Thus, some participants might have increased a particular item while some decreased in the same item, therefore, producing offsetting changes.

As outlined, the user types can not be considered stable after six months. Most of the participants have presented different dominant user types and also the results showed differences in the average scores of the user types in both phases. Our results demonstrate that when designing gamified environments based on user types it is necessary to measure the users' scores after a certain period. Personalization of gamified environments also needs to follow the user changes, guaranteeing that the personalization supports the user constantly.

4.2. Limitations

Our study has some limitations inherent to the type of study, which we seek to mitigate. Initially, the limited number of participants, as well as the fact that the participants are from the same country (*i.e.*, Brazil) can prevent the generalization of the results. To mitigate this limitation we used consolidated static methods for validating responses. To access all the necessary information about the respondents we used a questionnaire that might be considered long (32 questions) for the respondents, thus, to mitigate this limitation, we conducted a pilot study asking the participants if they considered the size of the questionnaire adequate for the research. It is possible that some participants might have not paid attention when answering the survey. To mitigate this limitation, all the respondents were volunteers and we inserted an "attention check question", eliminating responses from participants who missed this question. Finally, since we only used descriptive statistics, a further statistical investigation is necessary to improve our results, especially the results based on the demographic information.

4.3. Research agenda

Considering the obtained results and the limitations of this study, some possible studies can be conducted in the future. First, since this is an exploratory study and our results showed that the Hexad sub-scale for the Disruptor and Free Spirit presented reliability results slightly below the acceptable, and other studies have found similar results [19, 41], we believe this result might highlight **the necessity of the improvement of Disruptor and Free Spirit sub-scale or further analysis of these user types**. Also, the results highlight the **necessity of further investigation in each measurement Hexad item, psychometric modeling for the sets, and analysis of how the stability of personality traits can affect the changes of the user types.**

This study was conducted without considering a specific domain, and the gamification effects can vary according to the context [30]. Literature reviews [13, 28] have indicated before the necessity of studies in the gamification field that improve the understanding of the impact that the context presents in gamified settings. Thus, **we recommend that future studies replicate this study in specific contexts (*e.g.*, health, education, business) to analyze how the context affects the user type changes, furthering our results.**

Similar to other studies about player/user types [36, 19], we were able to access the user types of the respondents in different moments, and it was possible to identify that the number of participants tends to decrease when the research is conducted in more than one phase. One possible reason for the reduction of participants in our research is there was not any kind of intervention with the respondents between the study phases. Considering that the number of participants can reduce the exploratory power of the results [13], and prevent the generaliza-

Table 6
Research agenda summary

Recommendation	Motivation	Type of studies
Improvement of Disruptor and Free Spirit sub-scale	Increase the reliability results	Exploratory/surveys/factor analysis
Investigation of each measurement Hexad item	Analyze which Hexad item affects more the user changes	Exploratory/surveys
Investigation about the stability of personality traits in the respondents	Analyze how the stability of personality traits affects the stability of the user type	Exploratory/surveys
Replicate the study in different areas	Analyze whether contexts affect the stability of the user type	Exploratory/surveys
Replicate the study increasing the number of participants and interventions	Increase the reliability results and generalization power	Exploratory/surveys
Predict how user types have changed over time	Avoid the need to repeatedly apply questionnaires and facilitate the personalization process	Exploratory/surveys/machine learning analysis

tion of the results, we recommend that **future studies should be conducted with a larger sample and with interventions between the phases**.

Similar to Busch *et al.* [36], we waited six months to analyze if the respondents have presented any difference in their user types. It is important to analyze if the participants can present changes in their user type earlier (*e.g.*, after two or three months), as well as if the respondents can return to the first user type after a longer period (*e.g.*, after a year). We suggest that **future studies should have more phases (*e.g.*, two months, a year), considering the evaluation of the user types stability in a shorter and longer period**.

Our study identified there were differences between most of the respondents' user types after six months, confirming the hypothesis that the profile of people changes (after six months) and directly influencing the style of personalization that should be carried out (*i.e.*, demonstrating the importance of dynamic personalization). Although recent studies [55, 45] showed that the prediction of the Hexad user types might be a possibility, the user type is still mostly accessed through surveys and questionnaires [28]. Considering that our results imply having to constantly analyze the users' type, making the process more costly by making users need to answer the questionnaire constantly, **future studies should be done to try to predict people's user type based on interaction data, machine learning, or based on the questionnaire response the first time (*i.e.*, predict what the user will be after a certain time, based on questionnaire responses only once)**.

In Table 6 we summarize the research agenda.

5. Concluding remarks

In this study, divided into two different phases, we conducted a comparison of 74 people's user types, to analyze if they can be considered stable. We used the Gamification User Types Hexad to access the participants' user types (Achiever, Philanthropist, Socialiser, Free Spirit, Player, and Disruptor) and conducted the second research phase after six months of the first phase. Our main results showed that the dominant user type of most of the participants has changed over time. Also, when comparing the average scores of the participants' user types in both phases, the average scores were different, indicating that changes happened between the phases. These results demonstrate that when designing a gamified environment based on the user type, it is important that this design can support user type's changes since the user types can not be considered stable. As future studies, we aim to focus on measuring the user types changes after a different period (*i.e.*, a year) and with people with a different demographic background (*i.e.*, more than one country). Also, since this study was exploratory, we intend to do further statistic analysis (*e.g.*, by using Structural Equation Modeling) about all the variables of each Hexad sub-scale and work in predict the user changes from the previously collected information.

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APPENDIX

B

THE RELATIONSHIP BETWEEN THE HEXAD USER TYPES AND GAMIFICATION DESIGNS IN THE EDUCATIONAL CONTEXT

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The relationship between user types and gamification designs

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Abstract
Gamification has been discussed as a standout approach to improve user experience, with different studies showing that users can have different preferences over game elements according to their user types. However, relatively less is known how different kinds of users may react to different types of gamification. Therefore, in this study ($N = 331$) we investigate how user orientation (Achiever, Disruptor, Free Spirit, Philanthropist, Player, and Socializer) is associated with the preference for and perceived sense of accomplishment from different gamification designs. Beyond singular associations between the user orientation and the gamification designs, the findings indicate no comprehensive and consistent patterns of associations. From the six user orientations, five presented significant associations: Socializer orientation was positively associated with Social, Fictional, and Personal designs, while negatively associated with Performance design; Player orientation was positively associated with Social (Accomplishment), Personal, and Ecological designs, while negatively associated with the Social design (Preference); Disruptor orientation was positively associated with Social design; Achiever orientation was positively associated with Performance and Social designs; and Free Spirit orientation was negatively associated with Social design. Based on the results, we provide recommendations on how to personalize gamified systems and set further research trajectories on personalized gamification.

Keywords User modeling · Personalization · Gamification · Hexad · Gameful experience

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1 Introduction

Gamification has been widely used in recent years to increase users' motivation in different areas, such as health (Johnson et al. 2016), virtual reality (Hassan et al. 2020), and education (Barata et al. 2013; Turan et al. 2016; Araya et al. 2019). According to Koivisto and Hamari (2019), the education/learning context is the most common in studies about gamification, and most have reported positive results. One goal of the use of gamification in education is to lead students to desired psychological outcomes (e.g., engagement, motivation, fun, or autonomy (Majuri et al. 2018)); however, some studies have also reported that gamification can have negative effects on students' behavior (Hanus and Fox 2015; Toda et al. 2017; Bai et al. 2020).

One of the main hypotheses for these negative effects is that people have different player types (i.e., different characteristics and preferences over game elements (Nacke et al. 2014)), which leads to different perceptions regarding the gamification design (Lavoué et al. 2018; Hallifax et al. 2019b; Oliveira et al. 2020), that can positively or negatively be affected by some of the game's elements (Oliveira and Bittencourt 2019b). At the same time, most of the gamified systems are developed in a way called "one size fits all", which means that the users' preferences are ignored and normally the designers create a universal gamified environment to suit all users (Tondello et al. 2017b; Oliveira et al. 2018), thus possibly negatively affecting their experience (Tondello et al. 2017b; Lavoué et al. 2018; Rodrigues et al. 2019).

Although in the past few years researchers have conducted some studies about personalized gamification (Hallifax et al. 2019a; Klock et al. 2020; Rodrigues et al. 2020), they have not reached a consensus about which game elements would be the most suitable for each player/user type, have used a small number of game elements, or have analyzed the relation of user types and game elements individually (Hallifax et al. 2019b; Klock et al. 2020). The relation of user types and sets of game elements demonstrated in the study conducted by Tondello et al. (2016) showed that the user types could be related with sets of game elements, rather than individual game elements. When we consider the way that the game elements are selected, most of the studies about personalized gamification select the game elements deliberately or by using literature reviews, which can bring some limitations (*e.g.*, the use and random naming of game elements that are correlated, or the exclusion of a game element that would be suitable for the context) (Klock et al. 2020; Rodrigues et al. 2020). Thus, one gap in the personalized gamification of gamified systems is studies about the preference for gamification designs (sets of game elements grouped according to their characteristics or purpose) for each user type and if they are positively affected by these gamification designs.

We tackled this challenge through a study with 331 participants, where we (1) identified their user types, (2) analyzed their preferences regarding different gamification designs (represented in storyboards), (3) measured the participants' preference and perceived sense of accomplishment in each gamification design, and (4) analyzed the participants' preference and perceived sense of accomplishment according to their user orientations, thus advancing toward answering the question: **How are user types associated with preference and perceived sense of accomplishment in different gamification designs?** Our results allow us to move toward evidence-based gamification design, generating new insights for gamification designers to create more effective gamified systems according to the users' preferences and experiences. We also provided a series of validated storyboards to represent the design concept of personalized gamified educational system.

This article is structured as follows: In Sect. 2, we present the study background, including an overview of player/user typologies, the gamification taxonomy used to select game elements, the gameful experience and why we measured one of its dimensions, and the main related work. Following on, we describe in Sect. 3 how the study was conducted, the construction and validation of the storyboards to represent the gamification designs, the survey's construction and application, and the main characteristics of the participants. In Sect. 4, we present and discuss the data collected and our statistical results. We also present the limitations of our study, as well as recommendations for future studies. Finally, in Sect. 5 we present the final remarks of our study.

2 Background

This section presents our study background (*i.e.*, player/user types, gamification taxonomies, and gameful experience), as well as the main related works.

2.1 Player/user types

Throughout the years, researchers have worked on how certain characteristics may affect the user's engagement while using a gamified system (Ferro et al. 2013) and how people can be grouped into player types (Yee 2006; Nacke et al. 2011). One of the first player type models was presented by Bartle (1996), which proposed a classification of four player types: (1) Achiever; (2) Explorer; (3) Killer; and (4) Socializer. Based on Bartle's player types, Yee (2006) proposed an empirical model of player motivations, based on data collected from 3000 Massive Multiplayer Online Role Playing Games (MMORPGs). In his analysis, Yee revealed ten motivation sub-components (Advancement, Mechanics, Competition, Socializing, Relationship, Teamwork, Discovery, Role-Playing, Customization, and Escapism), which he grouped into three overarching components (Achievement, Immersion and Social).

Another player type model that has been used in researches is the BrainHex Model (Nacke et al. 2011), which was based on neurobiological findings and has seven player types: (1) Seeker; (2) Survivor; (3) Daredevil; (4) Mastermind; (5) Conqueror; (6) Socializer; and (7) Achiever. According to Nacke et al. (2011), each player type from the BrainHex model should be understood not as a psychometric type, but rather as an archetype that typifies a particular player experience.

To create a model designed specifically for gamification, Marczewski (2015) proposed the Gamification User Types Hexad, with six user types motivated by intrinsic or extrinsic motivational factors. The user type division in intrinsic and extrinsic motivation is based on the self-determination theory (SDT) that says that people are intrinsically motivated when the activity supports three basic human psychological needs (competence, autonomy and relatedness), or extrinsically motivated when the reason for doing something is not an interest in the activity itself (Deci and Ryan 1985). According to Diamond et al. (2015) and Tondello et al. (2016), the user types motivated by intrinsic motivations are the (1) Socializers; (2) Free Spirits; (3) Achievers; and (4) Philanthropists, while (5) Players are motivated by extrinsic motivations. The (6) Disruptors are not a user type derived from SDT, but from the observation of user behavior within online systems (Tondello et al. 2019).

The Hexad has been chosen for our study since it is considered the most appropriate user typology for tailoring gamification (Hallifax et al. 2019b), it does not classify the user in one specific user type (users are classified in more than one user type, with a principal tendency followed by others in some degree (Tondello et al. 2016)), and the model is empirically validated (Tondello et al. 2019), was created especially for gamification (Marczewski 2015), and has been successfully used in other recent studies (Orji et al. 2018; Lopez and Tucker 2019; Mora et al. 2019; Hallifax et al. 2020).

2.2 Gamification taxonomy

Even though there are several gamification frameworks (Azouz and Lefdaoui 2018), only a few of them are developed for the educational context (Toda et al. 2019). To help designers, teachers and instructors select and understand how game elements can be used in the educational context; Toda et al. (2019) created a gamification taxonomy composed of twenty-one game elements that could be used in gamified educational environments, organizing them in five dimensions. The **Performance/Measurement** dimension is related to the environment response and has the elements Point, Progression, Level, Stats, and Acknowledgement. The **Ecological** dimension is related to the environment that the gamification is implemented in, and is formed by the elements Chance, Imposed Choice, Economy, Rarity, and Time Pressure. The **Social** dimension is related to the interactions between the learners presented in the environment and has the elements Competition, Cooperation, Reputation, and Social Pressure. The **Personal** dimension is related to the learner that is using the environment and has the elements Sensation, Objective, Puzzle, Novelty, and Renovation. Finally, the **Fictional** dimension is the mixed dimension that is related to the user and the environment and has the elements Narrative and Storytelling.

As far as we know, this taxonomy is the only one that has been developed and validated for the educational context, explaining a considerable number of game elements, and grouped them into dimensions. Considering that the deliberate selection of game elements can lead to the use of different game elements with the same goal

(Rodrigues et al. 2020), we decided to use Toda's taxonomy to select the game elements for the storyboards' design for this study.

2.3 Gameful experience

The success of gamification depends of the gameful experience[1] the service creates in the user (Eppmann et al. 2018). Also, new generations seem to be more susceptible to having gameful experiences (Högberg et al. 2019), showing that its measurement can be an important part of the future design of gamified environments.

Högberg et al. (2019) presented a validated instrument for measuring the gameful experience users can have while using a system or a service. They also identified seven dimensions that describe the gameful experience: Accomplishment, Challenge, Competition, Guided, Immersion, Playfulness, and Social experiences. The instrument is formed of 56 questions and can be used for adaptive gamification and user-modeling research in gamification contexts.

The accomplishment dimension is defined as experiencing the demand for successful performance, goal achievement and progress (Högberg et al. 2019). Users can be motivated to complete a goal or task for the pleasure of feeling accomplished, as there is a specific type of intrinsic motivation that leans toward accomplishment (Vallerand et al. 1992; Barkoukis et al. 2008). In our study, we focused on the measurement of this dimension because it can reflect the users' engagement and can be considered as a long-term experience that extends beyond the use of the service, which can be essential to achieving the goal of gamification (Högberg et al. 2019).

2.4 Related work

Different studies have been conducted to relate users with game elements considering gamification in general, and also in specific domains (Koivisto and Hamari 2019). Moreover, the personalization of gamification has been the object of some literature reviews conducted over recent years (Hallifax et al. 2019a; Klock et al. 2020; Rodrigues et al. 2020). We used these literature reviews to conduct a snowballing review to find studies that have looked at how player/user typologies can be related to game elements in the educational context. In this section, we briefly discuss some of these recent studies.

Using the BrainHex typology, Monterrat et al. (2017) proposed a model and an adaptation process to gamify learning environments to increase learners' motivation. They tested the adaptation process with 59 middle school students, where they showed that different player types have different preferences and perceptions for game elements. They also showed that increasing the game elements in an environment also increases the perceived complexity of the environment for the students.

[1] In this study, we used the definition proposed by Landers et al. (2019): "A psychological state where the user perceives non-trivial achievable goals created externally, is motivated to pursue them under an arbitrary set of behavioral rules, and evaluates that motivation as voluntary".

Lavoué et al. (2018) conducted an experiment with 266 participants, and according to their player types, they adapted the gamification features that were displayed in the interface of an online learning environment. Their results showed that the participants with the adapted features and counter-adapted features had similar values in their enjoyment, although the adapted features improved the participation of learners who used the environment for more time, and reduced the learners' level of amotivation when compared to counter-adaptive gamification. Oliveira and Bittencourt (2019a) conducted an empirical experiment with 121 elementary students to identify the students' preferences for game elements according to their BrainHex player type. Corroborating the results of Monterrat et al. (2017), they also identified that students had different preferences for the game elements according to their player type. They further suggested a guideline to design or adapt gamified educational environments based on the BrainHex player type and ten game elements. Daghestani et al. (2020) used gamification, classification, and adaptation techniques to study the impact of gamification on students' engagement and learning. From three different groups of students (control group, gamified group, and adaptive-gamification group), they showed that the students who used an adaptive-gamified system presented a better performance than the students who used the gamified system, and that the gamification and adaptive-gamification had a positive effect on students engagement. The adaptive-gamified system was tailored based on ten game elements and BrainHex player types.

One of the first studies to use Hexad to explore the user type was conducted by Gil et al. (2015). Their study used an initial version of the Hexad (with four user types: Achievers, Socializers, Explorers, and Philanthropists) to correlate the user types with 19 game elements and 21 students' actions in an e-learning environment. They conducted a user study with students from a 1st-year course of Computer Science, where the students could freely choose their actions in the e-learning environment. Their results showed that for all of the user types except Explorer, the students' actions and game elements were related to the correspondent user types. Tondello et al. (2016) analyzed the correlation between the Hexad user types and 32 game elements, based on the preference of students from the University of Waterloo. Using the Hexad suggestion (Marczewski 2015), they also grouped the 32 game elements into six sets (one for each user type), analyzing the correlation with the correspondent user type. They found positive correlations between almost all the Hexad user types and the proposed game elements, except the Philanthropists. Based on their results, they created a new association table, suggesting a set of game elements for each Hexad user type. Hallifax et al. (2020) conducted a study with students from high schools, tailoring six game elements with their Hexad user types and the initial motivation user model. Considering the results of tailoring gamification based only on the Hexad user types, they found that students were more engaged in the learning task when they used game elements tailored for their user types. Furthermore, this higher level of engagement was associated with lower student performances, and their results showed that an adaptation based only on player types had no effect on learner motivation to learn Mathematics.

Even though our gamification designs demonstrated instructional content in gamified education, we did not limit the educational level of the respondents as most of the related works did (Gil et al. 2015; Tondello et al. 2016; Monterrat et al. 2017; Oliveira and Bittencourt 2019a; Daghestani et al. 2020; Hallifax et al. 2020). Also, while all of the studies featured in our related works selected the game elements based on other studies (Monterrat et al. 2017; Lavoué et al. 2018; Daghestani et al. 2020), most used in literature (Oliveira and Bittencourt 2019a; Hallifax et al. 2020), or in the suggestion of the user typology (Gil et al. 2015; Tondello et al. 2016), we selected the game elements based on a gamification taxonomy created specifically for educational environments. Except for the study conducted by Tondello et al. (2016), all of the studies only evaluated the correlation of the user types with the game elements individually. Thus, as far as we know, our study is the first to conduct an empirical study evaluating respondent preference regarding different gamification designs (a group of strategically organized game elements) in educational settings, considering a gamification-based user typology, a validated taxonomy for the education domain, and also a dimension of the gameful experience. In Table 1, we present a comparison between the related works.

3 Study design

Our study aimed to identify whether the user orientations affect the preference and perceived sense of accomplishment for gamification designs in gamified systems. Thus our research question is: "**How are user orientations (Philanthropist, Achiever, Socializer, Free Spirit, Player and Disruptor) associated with preference and perceived sense of accomplishment in different gamification designs (Fictional, Personal, Performance, Social and Ecological)?**". To answer our research question, we organized our study in five different steps: (1) storyboards design; (2) survey design; (3) pilot study; (4) survey application; and (5) data analysis. Figure 1 summarizes the study design.

3.1 Materials and method

Before designing our survey, we needed to decide how to present the dimensions of the gamification taxonomy in a way that the respondents could imagine how their implementation would be in a real gamified system. As recommended in recent literature in the field of human-computer interaction (HCI), a good strategy is the use of storyboards (Orji et al. 2014; Altmeyer et al. 2019, 2020; Yassaee et al. 2019). Storyboards are a graphical depiction of a narrative (Truong et al. 2006) that can be used in HCI and design to illustrate interfaces and contexts of use, thus offering designers a possibility as a prototyping technique. The use of storyboards can help users perceive and interpret proposed functionalities (Truong et al. 2006), and also help to direct the respondents' focus (Yassaee et al. 2019). Given the benefits storyboards offer to collect user reactions to the system elements (Truong et al. 2006), that they can help with the collection of data from people with different backgrounds since they provide a visual language that facilitates user understanding (Orji et al. 2018), and that other recent gamification studies have used storyboards (Altmeyer

Table 1 Related works comparison

Study/Year	Typology	GE	SE	*P*	ME
Gil et al. (2015)	Hexad	19	Based on Hexad suggestion (Marczewski 2015)	40	Students' actions
Tondello et al. (2016)	Hexad	32	Based on Hexad suggestion (Marczewski 2015)	133	Preference for game elements
Monterrat et al. (2017)	BrainHex	3	Based on literature	59	Students' interactions with the game elements and perceived fun and usefulness
Lavoué et al. (2018)	BrainHex	5	Based on literature	266	Time spent in the environment, enjoyment and motivation
Oliveira and Bittencourt (2019a)	BrainHex	10	Based on most used in literature	121	Preference for game elements
Daghestani et al. (2020)	BrainHex	10	Based on literature	77	Students' interaction data and engagement
Hallifax et al. (2020)	Hexad	6	Based on most used in literature	258	Motivation and engagement
Our study	Hexad	21	Validated taxonomy for the educational context	331	Preference for game elements and perceived sense of accomplishment

Typology: player/user typology; GE: amount of game elements used; SE: way that the game elements were selected; *P*: number of participants; ME: what was evaluated (e.g., preference for game elements; flow, engagement)

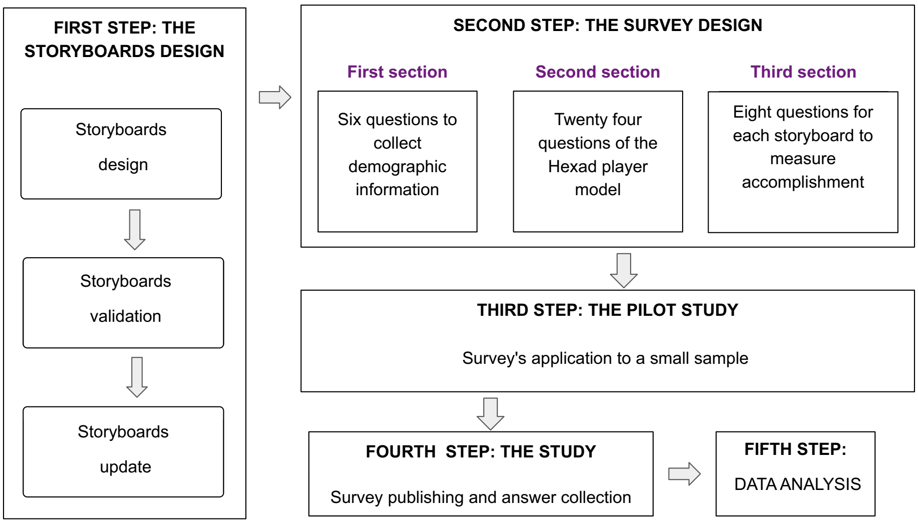


Fig. 1 Study design

et al. 2019; Yassaee et al. 2019; Altmeyer et al. 2020), we decided to implement five storyboards to represent each of the five dimensions proposed in Toda's taxonomy (Toda et al. 2019).

To design the storyboards[2], we followed the recommendations of Truong et al. (2006), which have been successfully used in recent similar studies (*e.g.*, Orji et al. (2017); Altmeyer et al. (2019); Brenes et al. (2019)). Truong et al. (2006) determined five attributes to design a storyboard: *i)* Level of detail; *ii)* Inclusion of text; *iii)* Inclusion of people and emotions; *iv)* Number of frames; and *v)* Portrayal of time. Thus, we created five storyboards with six frames each, representing a fictional learning environment without defining a specific curricular component. All of the 21 game elements of Toda's taxonomy (Toda et al. 2019) were used in the storyboards according to their dimension. Also, considering the own organization of the taxonomy to avoid overlapping, each one of the 21 game elements was represented only in one storyboard.

To ensure the storyboards quality, after the storyboards' design, they were evaluated by three gamification experts with extensive experience in evaluating this type of technology. Two experts had six years' experience in researching gamification, and one had nine years. To conduct the evaluation, we used a Likert scale (Likert 1932) that went from 1 (totally disagree) to 5 (totally agree), asking the experts about the storyboards. They had to answer the following questions: (1) "Does this storyboard represent the dimension?"; and (2)"How can we improve this storyboard?". This last was an open question, so they could give their impressions about the storyboard and tell us how to improve it.

[2] The storyboards were designed at: https://www.storyboardthat.com/.

Our main goal in this evaluation was to guarantee that the storyboards correctly represented the five dimensions proposed by Toda et al. (2019). In their evaluation, only one storyboard got an evaluation of 1 (totally disagree) in relation to the question “Does this storyboard represent the dimension?” by one of the experts. In the other storyboards, all of them evaluated as 5 (totally agree) or 4 (partially agree) for the same question. Then, we updated the storyboards according to their feedback to the question “How can we improve this storyboard?”: the gamification experts pointed out some game elements that were present in more than one storyboard, that the use of some figures could cause a negative feeling about a prize, and offered views on how we could improve the use of the game element Competition. The storyboards and their textual description can be seen in the Appendix.

After the evaluation and improvement in the storyboards, we designed the survey. The survey was composed of 71 questions organized in three different sections. (1) Demographic information: gender, age, education degree, and gaming habits. (2) User type identification: we used the Gamification User Types Hexad (Tondello et al. 2016), thus the respondents were asked to rate how well the 24-item scale proposed by Tondello et al. (2016) represented them. We used a 7-point Likert scale (Likert 1932), the questions were presented in a random order, and respondents could not identify the corresponding type (as recommended by Tondello et al. (2016)). Inspired by other studies (Orji et al. 2018; Hallifax et al. 2019b; Oliveira et al. 2020), in this part of the survey we used an “attention-check” question: “I like to be with my friends, but this question is just to evaluate your attention. Please, mark the option number 3, to let us know that you are paying attention”. This question was to ensure that the respondents were paying attention in the survey and reading all the items.

Finally, the last section was the (3) sense of accomplishment and preference measurement. In this step, we used the sub-scale proposed by Högberg et al. (2019) to measure the perceived sense of accomplishment for each gamification design. Following Högberg et al. (2019) recommendations, the respondents were asked to rate on a 7-point Likert scale (Likert 1932) how well each of the eight statements of the Accomplishment dimension represented their feelings about each gamification design. Besides the measurement of the perceived sense of accomplishment, the last question of the survey was “Which storyboard is your favorite?”. Thus, we were able to compare the perceived sense of accomplishment with the respondent’s preference for the gamification designs.

Before launching the survey, as recommended by Connelly (2008), we conducted a pilot study to assess whether the survey was being correctly understood by the respondents, as well as to assess whether the number of questions was adequate. This pilot group answered the survey before the survey application, with the question “Is this survey large?” added at the end of the survey. The pilot study was conducted with a small sample composed by 10 participants, where 80% answered that the survey wasn’t large so we decided to not take away any questions from it.

Table 2 Demographic information

Variable	%	Variable	%
Gender		*Age*	
Female	52	10–14	0.30
Male	47	15–19	9
Other	0.60	20–24	12
Preferred not to answer	0.60	25–29	15
Education level		30–34	18
Elementary/Middle School	2	35–39	13
High School	9	40–44	12
Bachelor	30	45–49	10
Specialized courses	21	50–54	7
M.Sc.	25	55–59	4
Ph.D.	8	Over 60	1
PostDoc	4	*Frequency*	
Gaming habits		Every day	13
Play games	67	Every week	21
Do not play games	33	Rarely	47
		I do not know	19

Table 3 Participants distribution, average scores and standard deviation

User types	*D* (%)	Mean score	S.D.	Female mean score	S.D.	Male mean score	S.D.
Philanthropist	35	24.18	4.78	23.86	5.47	24.50	3.89
Achiever	30	23.98	4.79	23.41	5.60	24.57	3.61
Free Spirit	12	22.50	4.63	22.23	5.30	22.71	3.74
Player	12	20.53	5.61	19.76	5.96	21.37	5.05
Socialzer	10	20.42	5.7	20.49	6.03	20.51	5.22
Disruptor	1	14.66	5.33	13.91	5.48	15.32	4.98

D Distribution of the dominant user types, *S.D.* standard deviation

3.2 Participants

The final survey was released on March 26, 2020, and was spread by social networks and e-mail. The survey was open for thirty-eight days and we received 366 answers, which 331 were valid according to our attention-check question. The respondents participated voluntarily, since we did not offer any kind of remuneration or gifts to the respondents. The study sample size is adequate under different aspects considering this type of study. According to the definitions of Bentler and Chou (1987) and Hair et al. (1998), it is necessary to have at least five participants for each construct measured (our study had seven constructs). Loehlin (1998) suggests a minimum sample of 100 participants for studies of this nature. Table 2 presents the demographic information of the respondents.

Table 4 Reliability results

Construct	Cronbach's α	Jöreskog's rho	Comp.R	Average V. E.
Achiever	0.881	0.887	0.918	0.736
Disruptor	0.679	0.664	0.726	0.426
Free spirit	0.755	0.768	0.845	0.578
Philanthropist	0.885	0.893	0.921	0.744
Player	0.880	0.886	0.918	0.737
Socialzer	0.808	0.818	0.874	0.635
SE	0.973	0.974	0.977	0.842
SF	0.962	0.964	0.968	0.791
SPF	0.974	0.974	0.977	0.844
SP	0.967	0.969	0.972	0.812
SS	0.977	0.978	0.980	0.859

Comp.R: Composite Reliability; Average V. E.: Average Variance Extracted; SF: Perceived sense of accomplishment for the storyboard Fictional; SP: Perceived sense of accomplishment for the storyboard Personal; SPF: Perceived sense of accomplishment for the storyboard Performance; SE: Perceived sense of accomplishment for the storyboard Ecological; SS: Perceived sense of accomplishment for the storyboard Social

Table 3 summarizes the participants' distribution by the dominant user types (i.e., the strongest tendency of the participants), the average scores, and the standard deviation for each Hexad user type. Resembling the HEXAD results of Marczewski (2020), our research identified that Philanthropist is the most common dominant user type and Disruptor is the least common dominant user type. Comparing the female and male scores in each Hexad user orientations (i.e., the tendencies of the participants), it is possible to identify that the male scores were higher than female scores in all of the Hexad user orientations.

4 Results

To ensure the instrument validation for our study, we first analyzed the data normality (using the Shapiro–Wilk test as recommended by Wohlin et al. (2012)), which showed that our data followed a non-normal distribution. Then, we measured the internal reliability for each Hexad sub-scale (user types in the survey), as well as for the perceived sense of accomplishment evaluation in each storyboard. Overall, the reliability was acceptable ($\alpha \geq 0.70$, RHO A ≥ 0.70, CR ≥ 0.70, AVE ≥ 0.50) for all storyboards and user orientations, except for the Disruptors. We also measured the discriminant validity finding acceptable values, considering that the square root of the variables' AVE value was larger than the correlations that the variable had with the other variables, and all of the variables presented correlations between them below 0.85. The reliability results are shown in Table 4, and the discriminant validity is shown in Table 5.

To answer our research question and measure the effects of the personalized gamification designs in terms of sense of accomplishment and preference, following

Table 5 Discriminant Validity (complete bootstrapping, sample=5000)

	AccE	AccF	AccPF	AccP	AccS	A	D	F	P	R	PrE	PrF	PrPF	PrP	PrS	S
AccE	0.918															
AccF	0.474	0.889														
AccPF	0.614	0.550	0.919													
AccP	0.620	0.623	0.639	0.901												
AccS	0.652	0.545	0.638	0.574	0.927											
A	0.367	0.400	0.480	0.389	0.429	0.858										
D	0.209	0.246	0.255	0.262	0.254	0.499	0.653									
F	0.268	0.369	0.369	0.294	0.322	0.740	0.539	0.760								
P	0.353	0.385	0.441	0.385	0.386	0.771	0.398	0.696	0.862							
R	0.313	0.280	0.349	0.302	0.369	0.563	0.425	0.511	0.413	0.797						
PrE	0.054	− 0.134	− 0.134	− 0.094	− 0.045	− 0.042	− 0.078	0.015	0.002	− 0.041	1.000					
PrF	− 0.074	0.142	− 0.130	0.017	− 0.091	0.000	− 0.079	− 0.030	− 0.021	0.010	− 0.161	1.000				
PrPF	− 0.003	− 0.079	0.183	− 0.070	− 0.047	0.045	0.086	0.048	0.010	0.034	− 0.343	− 0.260	1.000			
PrP	0.030	0.037	0.030	0.135	− 0.014	− 0.008	− 0.044	0.026	− 0.025	0.096	− 0.153	− 0.116	− 0.248	1.000		
PrS	− 0.011	0.077	− 0.011	0.053	0.165	− 0.008	0.059	− 0.061	0.019	− 0.074	− 0.273	− 0.207	− 0.441	− 0.197	1.000	
S	0.306	0.444	0.364	0.356	0.451	0.559	0.310	0.541	0.665	0.393	− 0.070	− 0.024	− 0.075	− 0.048	0.192	0.858

P: Philanthropist; A: Achiever; R: Player; F: Free Spirit; S: Socialzer; D: Disruptor; AccE: Perceived sense of accomplishment for the storyboard Ecological; AccF: Perceived sense of accomplishment for the storyboard Fictional; AccPF: Perceived sense of accomplishment for the storyboard Performance; AccP: Perceived sense of accomplishment for the storyboard Personal; AccS: Perceived sense of accomplishment for the storyboard Social; PrE: Preference Ecological; PrF: Preference Fictional; PrPF: Preference Performance; PrP: Preference Personal; PrS: Preference Social

Table 6 Comparison between the favorite storyboard and the perceived sense of accomplishment

Storyboard	Preference (%)	Accomplishment (%)	Female Acc (%)	Male Acc (%)
Fictional	11	14	15	13
Personal	10	12	13	11
Performance	36	28	27	30
Ecological	18	21	20	22
Social	26	25	25	25

Preference: Which storyboard did you prefer?; Accomplishment: Perceived sense of accomplishment; Female Acc: Perceived sense of accomplishment by the female respondents; Male Acc: Perceived sense of accomplishment by the male respondents

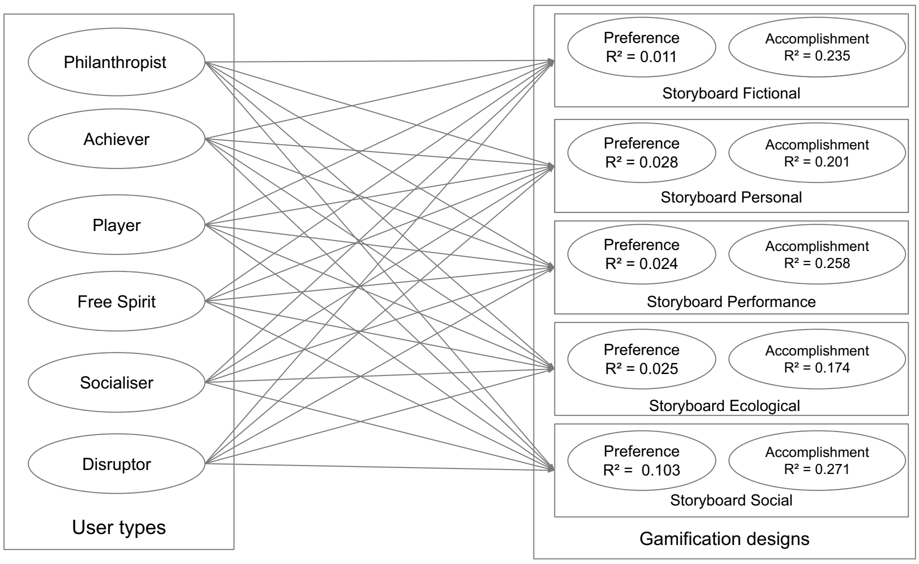


Fig. 2 Research model

other recent studies in personalized gamification (Orji et al. 2018; Hallifax et al. 2019b; Stuart et al. 2020), we employed the Partial Least Squares Path Modeling (PLS-PM) analysis to identify the relation between the Hexad user types with the gamification designs (sense of accomplishment and preference), since it is a reliable method for estimate cause-effect relationship models with latent variables (Hair Jr et al. 2016). To perform the statistical analysis in our study, we used SPSS 26 software. To conduct the PLS-PM, we used SmartPLS[3] software, that provides a graphical interface to calculate PLS-PM (Wong 2013). Our complete dataset can also be found in the complementary files.

[3] https://www.smartpls.com/.

Table 6 presents the preference and perceived sense of accomplishment averages in general and by gender. It is possible to identify that the Performance gamification design is the most chosen in terms of preference and perceived sense of accomplishment.

The research model of our study is shown in Fig. 2. The results indicate that the **Achiever** orientation is positively associated with perceived sense of accomplishment from the Performance ($\beta = 0.295$***), and Social ($\beta = 0.238$*) designs. The **Player** orientation is positively associated with perceived sense of accomplishment from Ecological ($\beta = 0.162$*) and Social ($\beta = 0.161$*) designs; positively associated with preference from Personal ($\beta = 0.165$**) design; and negatively associated with preference from Social ($\beta = -0.148$*) design. The **Free Spirit** orientation is only negatively associated with preference from Social ($\beta = 0.150$*) design. The **Socializer** orientation is positively associated with perceived sense of accomplishment from Fictional ($\beta = 0.307$***), Personal ($\beta = 0.154$*) and Social ($\beta = 0.309$***) designs; positively associated with preference from Social ($\beta = 0.370$***) design; and negative associated with preference from Performance ($\beta = -0.165$*) design. The **Disruptor** orientation is positively associated with preference from Social ($\beta = 0.150$*) design. The **Philanthropists** orientation did not present any association. All of the relations are shown in Table 7.

4.1 Discussion

The goal of this study was to understand the relationship between user orientations (Achiever, Disruptor, Free Spirit, Philanthropist, Player, and Socializer) and gamification designs (Fictional, Personal, Performance, Ecological, and Social). Overall, we identified different positive and negative associations between five of the six user orientations with the gamification designs. However, we identified that there is no consistent pattern of associations.

In terms of the user type distribution, our results (see Table 3) are similar to the results of Marczewski (2020), with Philanthropist as the most common dominant user type and Disruptor as the least common dominant user type. Also, our results are similar to the results found by Tondello et al. (2019), where they identified that Philanthropist and Achiever are the prevalent user orientations and Disruptor was the one that scored lower. According to Tondello et al. (2019), women tend to score higher than men in all the user orientations with intrinsic motivations (i.e., Philanthropist, Socializer, Free Spirit, and Achiever), and even though in our results men scored higher than women in all the user orientations, the difference was smaller in the Philanthropist, Socializer, Free Spirit, and Achiever orientations (i.e., the user orientations that are motivated intrinsically).

Starting to answer our research question, considering the effects of personalized gamification designs on user orientations' sense of accomplishment and preference (see Table 7), similar with the results found by Hallifax et al. (2019b) and Tondello et al. (2016), our results showed that **Philanthropists** did not present a significant association with any gamification design. Moreover, our results showed that Philanthropists presented a negative association with the Fictional gamification design in

Table 7 Results: associations between gamification designs and user orientation

	β	P-value	CI			β	P-value	CI	
			2.5%	97.5%				2.5%	97.5%
PAcc → SF	− 0.006	0.951	− 0.176	0.198	AAcc → SF	0.157	0.110	− 0.035	0.333
PPr → SF	− 0.029	0.765	− 0.214	0.172	APr → SF	0.080	0.444	− 0.121	0.281
PAcc → SP	0.164	0.063	− 0.029	0.342	AAcc → SP	0.168	0.066	− 0.027	0.314
PPr → SP	− 0.013	0.890	− 0.209	0.171	APr → SP	− 0.064	0.515	− 0.234	0.105
PAcc → SPF	0.149	0.082	− 0.028	0.304	AAcc → SPF	0.295***	0.001	0.119	0.456
PPr → SPF	0.020	0.852	− 0.193	0.216	APr → SPF	0.047	0.667	− 0.159	0.255
PAcc → SE	0.166	0.069	− 0.004	0.338	AAcc → SE	0.174	0.075	− 0.012	0.346
PPr→ SE	0.119	0.242	− 0.086	0.317	APr→ SE	− 0.113	0.315	− 0.329	0.079
PAcc → SS	0.005	0.956	− 0.146	0.176	AAcc → SS	0.238*	0.011	0.049	0.420
PPr → SS	− 0.095	0.309	− 0.261	0.056	APr → SS	0.034	0.724	− 0.143	0.214
RAcc → SF	0.030	0.627	− 0.095	0.154	FAcc → SF	0.058	0.429	− 0.082	0.206
RPr → SF	0.042	0.613	− 0.115	0.182	FPr → SF	− 0.021	0.804	− 0.210	0.133
RAcc → SP	0.109	0.101	− 0.031	0.241	FAcc → SP	− 0.132	0.127	− 0.291	0.062
RPr → SP	0.165**	0.002	0.048	0.261	FPr → SP	0.104	0.261	− 0.093	0.298
RAcc → SPF	0.117	0.062	− 0.004	0.230	FAcc → SPF	− 0.063	0.351	− 0.193	0.081
RPr → SPF	0.009	0.892	− 0.124	0.123	FPr → SPF	0.040	0.661	− 0.139	0.244
RAcc → SE	0.162*	0.014	0.033	0.310	FAcc → SE	− 0.124	0.142	− 0.281	0.036
RPr→ SE	− 0.005	0.946	− 0.138	0.140	FPr→ SE	0.145	0.066	− 0.032	0.276
RAcc → SS	0.161*	0.012	0.021	0.291	FAcc → SS	− 0.128	0.154	− 0.299	0.037
RPr → SS	− 0.148*	0.031	− 0.270	− 0.008	FPr → SS	− 0.226**	0.009	− 0.386	− 0.073
SAcc → SF	0.307***	0.000	0.171	0.437	DAcc → SF	0.031	0.644	− 0.091	0.154
SPr → SF	− 0.021	0.803	− 0.190	0.127	DPr → SF	− 0.108	0.189	− 0.260	0.036
SAcc → SP	0.154*	0.036	0.004	0.297	DAcc → SP	0.090	0.231	− 0.055	0.239
SPr → SP	− 0.092	0.284	− 0.259	0.083	DPr → SP	− 0.104	0.166	− 0.250	0.030
SAcc → SPF	0.087	0.204	− 0.042	0.231	DAcc → SPF	0.006	0.916	− 0.085	0.123
SPr → SPF	− 0.165*	0.032	− 0.305	− 0.025	DPr → SPF	0.081	0.258	− 0.072	0.223
SAcc → SE	0.094	0.186	− 0.052	0.229	DAcc → SE	0.026	0.732	− 0.115	0.174
SPr→ SE	− 0.130	0.081	− 0.270	0.005	DPr→ SE	− 0.104	0.139	− 0.222	0.025

Table 7 (continued)

	β	*P*-value	CI			β	*P*-value	CI	
			2.5%	97.5%				2.5%	97.5%
SAcc → SS	0.309***	0.000	0.155	0.446	DAcc → SS	0.038	0.564	− 0.077	0.165
SPr → SS	0.370***	0.000	0.259	0.467	DPr → SS	0.150*	0.017	0.023	0.254

*p < 0.1, **p < 0.05, ***p < 0.01; β: Regression Coefficient; CI: Confidence Interval; PAcc: Philanthropist perceived sense of Accomplishment; PPr: Philanthropist Preference; AAcc: Achiever perceived sense of Accomplishment; APr: Achiever Preference; RAcc: Player perceived sense of Accomplishment; RPr: Player Preference; FAcc: Free Spirit perceived sense of Accomplishment; FPr: Free Spirit Preference; SAcc: Socialzer perceived sense of Accomplishment; SPr: Socialzer Preference; DAcc: Disruptor perceived sense of Accomplishment; DPr: Disruptor Preference; SF: Storyboard Fictional; SP: Storyboard Personal; SPF: Storyboard Performance; SE: Storyboard Ecological; SS: Storyboard Social

terms of perceived sense of accomplishment and preference, the only design that did not present the "assistant" that explained what the student would do in that gamification design. Since the Philanthropists are motivated by interaction with others (Tondello et al. 2016), we believe the lack of the "assistant" presence can be understood by Philanthropists as a lack of interaction.

Analyzing our results in comparison with other studies (Tondello et al. 2016, 2017a), we believe that **Achievers** had a strong significant association with the Performance and Social gamification designs in the perceived sense of accomplishment measurement, especially because these two designs showed game elements and situations that could lead the user to feeling achievement and to demonstrate competence, which intrinsically motivates this user type (Tondello et al. 2016). We believe that when implemented in a gamified system, the Performance (game elements: Level, Point, Progression, Stats, and Acknowledgement) and Social (game elements: Social Pressure, Competition, Social Status, and Cooperation) gamification designs would probably lead the Achievers to have a feeling of advancement in their skills, and thus motivate them.

Since **Players** are motivated by extrinsic rewards (Tondello et al. 2016), we believe that the significant associations with the Ecological gamification design were related to the game elements of Rarity and Economy. Orji et al. (2018) found that Players tend to be motivated by Competition and Cooperation, which can explain the positive significant association with the Social gamification design in terms of perceived sense of accomplishment. At the same time, Players presented a slight and negative significant association with the Social gamification design in terms of preference. Thus, even though the Social gamification design brought a sense of accomplishment to the Players, this gamification design was not preferred by them. Players also presented a positive significant association with the Personal gamification design, probably because the game element Puzzle (Challenge), related to this user type in other studies (Tondello et al. 2017a, 2016).

Free Spirits only presented one significant association with the Social gamification design; however, it was negative. Also, this user orientation was the one that presented more negative associations, since **we were able to identify that Free**

Spirits presented negative non-significant associations with all of the gamification designs. Considering preference, this user orientation presented negative non-significant associations with Fictional gamification design, and considering perceived sense of accomplishment, negative non-significant associations with Personal, Performance, Ecological, and Social gamification designs. This was unexpected considering that we presented game elements in this study that were related to this user type in previous studies (*e.g.* Puzzle (Tondello et al. 2017a, 2016) and Level (Tondello et al. 2017a)).

Socializers were the user orientation that presented more significant associations, including a strong significant association with the Social gamification design. The game elements presented in the Social gamification design are important to ensure interactions between the users (Toda et al. 2019) and can be related directly with the Socializers that are intrinsically motivated by relatedness (Tondello et al. 2019). **We understand that the Social gamification design, when implemented in a gamified system, could guide the Socializers into relatedness, which would motivate them.** The game elements of the Social gamification design (game elements: Social Pressure, Competition, Social Status, and Cooperation) have already been individually associated with Socializers in previous studies (Tondello et al. 2016; Marczewski 2017; Tondello et al. 2017a). Probably, the strong significant association with the Fictional gamification design occurred because the game element Narrative is related to the user's interaction with the system (Toda et al. 2019), and the slight significant association with the Personal gamification design because of the game element Puzzle (Challenge), that has been related with this user orientation before (Tondello et al. 2016). They also presented a slight and negative significant association with the Performance gamification design, probably because of the game elements showing progress in this gamification design, considering that similar results were found by Hallifax et al. (2019b).

We believe **Disruptors** presented a significant association with the Social gamification design, especially because of the game element Competition. Tondello et al. (2016) identified that competition is a game element that can be related with this user orientation, and Orji et al. (2018) showed that competition would motivate people with high disruptor tendencies. Also, the Social gamification design is the one that shows interactions with other students, and Disruptors need interactions to influence other users to try to change the system (Marczewski 2015). Hence, this can be another reason for this significant association.

Our results also presented some non-significant associations between the user orientations and the gamification designs that indicate some possibilities. As aforementioned, the Philanthropists presented a non-significant association with the Fictional gamification design. We believe that designers should guarantee that, especially when the gamified system does not present interactions with other users, they have at least a figure to simulate interaction (e.g., animated pedagogical agents or an "assistant" from the system). Considering the non-significant associations, Players presented a positive association in terms of perceived sense of accomplishment with Performance and Personal gamification designs. Since this user orientation also presented a significant association with the Personal gamification design in terms of preference, we understand that the implementation of this design would be a good option to increase the motivation of this user type. The association with the Performance gamification design could be explained by the use of the game elements Level and Point, related to this user type before (Tondello et al. 2016, 2017a). Therefore, the implementation of this design to Players also could be a good option to increase the sense of accomplishment in these users. The Disruptors presented a negative association with the Ecological, Personal, and Fictional gamification designs. The Personal and Fictional designs represented how the system would work; therefore, this could be seen by the Disruptors as the boundaries of the system. The game element Time Pressure, represented by a clock in the Ecological design, could also be seen by the Disruptors as a limitation of their actions. Since they are motivated by change (Tondello et al. 2016), we understand these designs could be understood by Disruptors as limiting, which could explain these negative associations.

Our results show that the perceived sense of accomplishment measurement has more homogeneous results than the preference measurement (see Table 6). This demonstrates that **only measuring the preference for game elements might not be sufficient to understand the effects of the game elements in user experience.** For instance, some user orientations presented a significant association with a gamification design in terms of perceived sense of accomplishment, but this not has happened in terms of preference with the same gamification design. Considering that the feeling of accomplishment drives the user to complete tasks or goals and reflects the user's engagement (Högberg et al. 2019), **we believe the user orientations that presented a significant association with a gamification design in terms of perceived sense of accomplishment can present better progress when using gamified systems that have that set of game elements.**

When we do not consider the user orientation, **the game elements of the Performance and Social gamification designs can be used for all users**, since these two designs showed a predominance in the preference and perceived sense of accomplishment results (see Table 6). Thus, **gamified systems must present the group of game elements that create interactions between the users, and the group of game elements that provide feedback to them.**

Our results corroborate other studies (Mora et al. 2019; Hallifax et al. 2019b; Tondello et al. 2017a) showing that **users have different preferences based on their user orientations**. Considering only preference by user orientation, the Social gamification design is strongly related with Socializers and can also be used with Disruptors, while the Personal gamification design can be indicated for Players. Furthermore, **the user orientation is a factor that affects how the users perceived their sense of accomplishment.** Considering the perceived sense of accomplishment and the user orientations, the Social and Performance gamification designs are the most related to Achievers, and Socializers seems to be strongly affected by the Social and Fictional gamification designs. **Philanthropists seem not to be affected by the game elements represented in this study, and Free Spirits might not be positively affected by most of the game elements.**

According to our results, it is possible to select the most appropriate gamification designs for each system user, according to their Hexad user type and based on two different approaches (preference and/or perceived sense of accomplishment). This can help designers to personalize gamification, and therefore positively affect

Table 8 Recommendations to personalize gamification

	Preference	Sense of accomplishment
Philanthropist	Ø	Ø
Achiever	Ø	+ SPF and + SS
Player	− SS and + SP	+ SE and + SS
Free Spirit	− SS	Ø
Socializer	− SPF and + SS	+ SF, + SP and + SS
Disruptor	+ SS	Ø

Ø: Without significant association; +: Significant positive association; −: Significant negative association; SF: Storyboard Fictional; SP: Storyboard Personal; SPF: Storyboard Performance; SE: Storyboard Ecological; SS: Storyboard Social

the users. To personalize gamified environments for people with higher **Achiever** tendencies, designers should focus on implementing the game elements from the Performance and Social gamification designs, since our results indicated a significant association in terms of perceived sense of accomplishment. The game elements from the Ecological and Personal gamification designs should be avoided since they presented a negative non-significant association. For people with higher **Disruptor** tendencies, designers should focus on implement the game elements from the Social gamification design, especially the game element Competition. Considering the non-significant associations this user orientation presented, if the gamified environment is based on the preference for game elements, it is important to avoid or use with caution the game elements from the Ecological, Personal, and Fictional gamification designs.

For people with higher **Player** tendencies, designers can focus on the game elements from the Personal and Ecological gamification designs. Since Players presented negative (preference) and positive (sense of accomplishment) significant associations with the Social gamification design, designers can give to these users the possibility to choose if they want to interact with the game elements from this gamification design. For people with higher **Socializer** tendencies, designers should focus on implementing the game elements from the Social gamification design, since this user type presented a significant association with this gamification design in both approaches (preference and sense of accomplishment). The game elements from the Personal and Fictional gamification designs can also be implemented to increase the experience for this user type. Game elements from the Performance gamification design should be avoided.

Since **Free Spirits** only presented a negative significant association with the Social gamification design, we indicate that the game elements from this gamification design should be avoided or used with caution. Considering the negative and non-significant associations this user type presented with the other gamification designs, we understand that designers could give users with high Free Spirit tendencies, a possibility to disable the game elements or to freely choose which game element each user would interact with. The **Philanthropists** did not present any significant association, therefore, designers can use the non-significant associations presented in our results to personalize gamified environments to this user type or also implement the possibility to disable the game elements or to freely choose which game element each user would interact with. Furthermore, we indicate that the system should provide interaction with other users or at least with the system itself, through an "assistant". In Table 8, we summarize these recommendations of which gamification designs can be used to personalize gamified systems based on the significant associations we found (see Table 7).

4.2 Limitations

Some limitations have emerged during the study and they need to be considered. Although the internal reliability for the Disruptors was below the acceptable threshold, we were able to identify that for this user orientation, there exists a kind of predominance: all of the Disruptors, except one, presented only this user orientation as the dominant user type, and we were not able to find any study that has reported similar results. As another observation, the use of gamification designs can bring different results from the use of a real gamified system. Our design focused on representing different phases a gamified system would have, thus, they were a design concept of a gamified system. While storyboards represent the "ideal" scenario to evaluate a design idea, the implementation brings other design decisions (Orji et al. 2014), which could influence the users' response. Also, two of the storyboards did not represent the moment the student would answer questions in the system, considering they were designed to show how a student would create a profile and also the moment that the student would know the system. Some respondents could see this as a gap, which could subsequently influence their responses in the survey.

We have sought to mitigate some of the foreseeable limitations during the conduct of the study. To mitigate the possibility that the storyboards do not represent the dimensions proposed by Toda et al. (2019), we validated the storyboards with three gamification experts before using them in the survey. The size of the survey could have led people to answer without paying attention, and to mitigate this threat, we used an "attention-check" question in the survey and eliminated the responses that did not pass this validation. As a final action, since the Hexad scale proposed by Tondello et al. (2019) and the Gameful Experience Questionnaire proposed by Högberg et al. (2019) were not empirically validated in Brazilian Portuguese, we conducted a statistical analysis to validate the answers obtained in our study to mitigate this threat.

4.3 Recommendations for future studies

Based on the results obtained in our study, as well as the limitations our study raised, it is possible to propose a series of new studies to deepen this research domain. Initially, our study focused on answering research questions in the field of education (i.e., using storyboards representing a gamified setting). At the same time, the effects of gamification may vary according to the field of application (*e.g.*, marketing, health, addictions, and others). Thus, we believe that **future**

studies should be conducted in different areas (*i.e.*, replicating our study in different domains) expanding our results by using specific gamification designs suited to the context.

Almost all the respondents were older than 15 years, which can prevent the results' generalization for younger people. We believe that **future studies should focus on people under 15 years old, analyzing if the age can change the preference and perceived sense of accomplishment**, thus expanding our results. Since most of the respondents had reported that they play games (67%), an interesting perspective **future studies should focus on is whether the gaming habit affects the preference and perceived sense of accomplishment in gamified systems.**

In our study, we chose to conduct an exploratory study which allowed us to have a broad view of the subject, without exercising control over our subjects. However, now that our results provide us with an overview of the subject, further studies must deepen the results through experimental studies in controlled environments, for example, directly comparing two gamification designs (personalized vs. non-personalized) in terms of user experiences. Therefore, we recommend that **future studies should conduct experiments comparing the effects of personalized with non-personalized gamification designs in the user types**.

In our study, we measured one dimension of the gameful experience (i.e., Accomplishment), and according to Högberg et al. (2019), the dimension of Immersion also seems to reflect user's engagement. Thus, future studies can be carried out to measure this dimension. This decision to look at the Accomplishment dimension of the gameful experience was important to obtain a reliable result for a specific dimension of the gameful experience. Now that we have these results, it may be necessary to assess the effects on other gameful experience dimensions (*e.g.*, Challenge, Competition, and Playfulness). Thus, we recommend that **future studies should investigate other gameful experience dimensions**.

Our results have allowed us to identify different significant (positive and negative) relationships between different user orientations and gamification designs. This means that future studies on the personalization of gamification can use these results as a basis for personalizing gamified environments. At the same time, it is also important to investigate whether the results obtained in this study are maintained in ecological environments (i.e., real gamified systems). Thus, we recommend that **future studies can implement the gamification designs proposed and validated in our study in gamified systems, and evaluate the effects of different versions of the system on the users' experience during the system usage**.

Also based on the results obtained in our study, it is possible to understand which gamification designs are more or less effective concerning the users' sense of accomplishment. This can be useful, for example, to enable gamified system designers to personalize the gamification in a way that positively affects users. To make this task easier for designers, we recommend that **future research may propose recommender systems** (Resnick and Varian 1997) **to suggest the most suitable gamification design for each user according to their Hexad user type.**

5 Concluding remarks

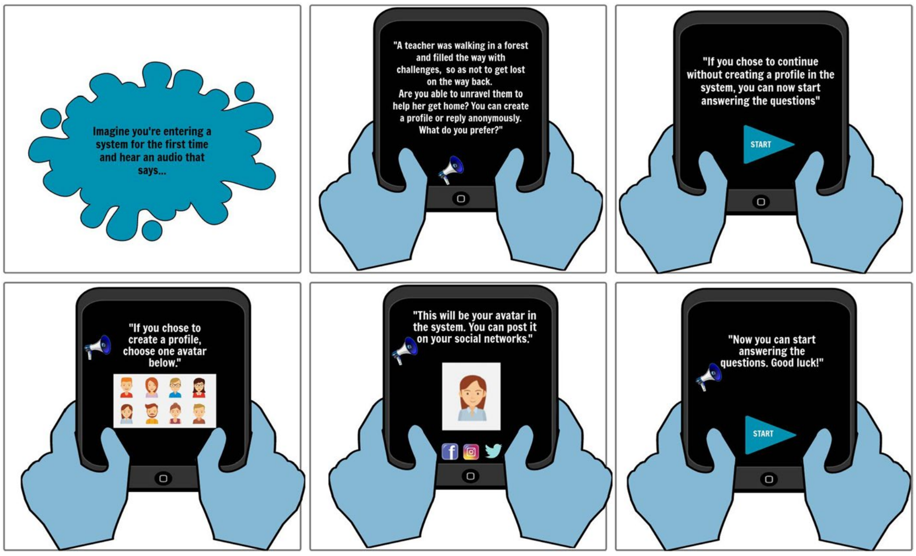
In this study, we presented how the six Hexad user orientations are related with five different gamification designs. To avoid the use of only the game elements that are considered the most used in research (e.g., points and badges), the game elements used in these designs were chosen from an empirically validated gamification taxonomy that groups twenty-one game elements in five dimensions. We used validated storyboards to show these dimensions to the respondents, in order to help people visualize how each dimension could be represented in a gamified system, instead of only asking about the preference for a particular dimension. Furthermore, we compared the preference with the perceived sense of accomplishment (a dimension of the gameful experience). Our results corroborate other research in identifying that the game elements presented in the Performance (Point, Progression, Level, Stats, and Acknowledgment) gamification design can be considered most adequate for all users, and that the Hexad user orientations have different preferences concerning gamification designs. Also, our results showed that the game elements presented in the Fictional (Narrative and Storytelling) and Personal (Objective, Puzzle, Novelty, Sensation and Renovation) gamification designs were the least preferred by the respondents. Our findings showed how some gamification designs can be used according to the user orientation, helping designers to design personalized gamified systems. For future studies, we intend to focus on the measurement of the other dimensions of the gameful experience, and how users that present more than one dominant user type are affected by the gamification designs.

Appendix

See Table 9 and Figs. 3, 4, 5, 6 and 7.

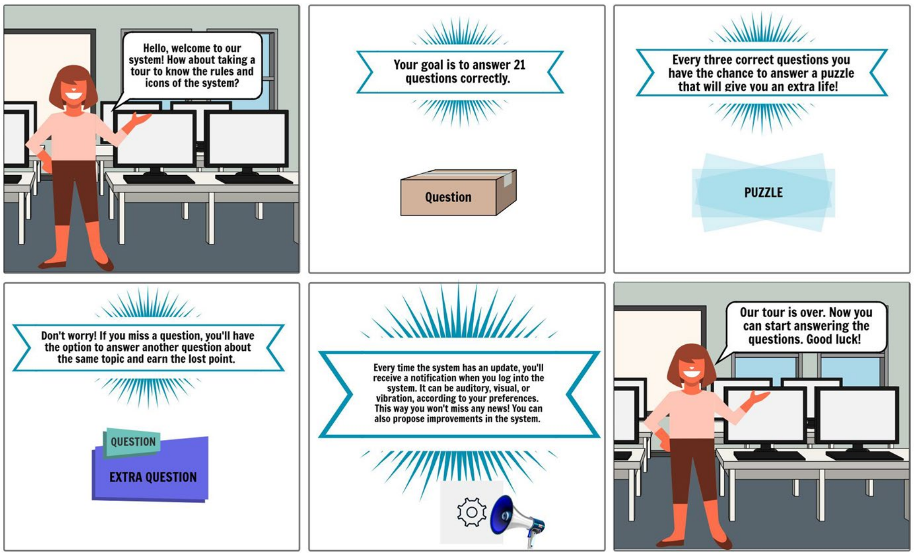
Table 9 Storyboards description

Dimension	Description
Fictional (SF)	This gamification design represents what would be the initial page of a gamified educational system. The student would hear an audio message explaining that a teacher spread questions along a path in a forest, so as not to get lost **(game element Storytelling)**. The student would be able to create a profile in the system, where they could create an avatar and share it in social networks, or start answering the questions without access to any bonus **(game element Narrative)**
Personal (SP)	This gamification design represents what would be the objectives and configurations of a gamified educational system. The student's goal would be to correctly answer twenty-one questions about certain content. This goal would be shown on the first screen of the gamified educational system **(game element objective)**. When missing a question about a certain subject, the student would have the option to do another question about the same subject and earn the lost point of the wrong question **(game element renovation)**. After three correct questions, the student would have the chance to answer a puzzle that would give them an extra life in the phase **(game element Puzzle)**. Every time the environment would have an update **(game element novelty)**, the user would receive an audible, visual, or vibration notification when logging into the system, according to the configuration he/she chooses **(game element sensation)**
Performance (SPF)	This gamification design represents how a gamified educational system would respond to the student's actions. The student would have to answer seven questions correctly to level up in the system and be a Beginner, Apprentice, or Master **(game element Level)**. When the student answers the questions correctly, he/she would receive XP's **(game element Point)** and would advance in the progression bar, represented by stars **(game element Progression)**. When the student answers more than ten questions correctly, he/she would receive a recognition trophy **(game element Acknowledgement)**. All of this information would be available on the page called "My progress" in the gamified educational system **(game element Stats)**
Ecological (SE)	This gamification design represents how a gamified educational system would engage the student to follow a desired behavior. The student would have to choose a specific path to follow **(game element Imposed Choice)**. After choosing the path, the student would spin a "wheel of luck" to earn a bonus, which could be "Skip a question", "Request a help letter" or "Increase the level of the phase by one hour" **(game element Chance)**. From there, they would have a limited time to finish the phase **(game element Pressure Time)**, where if they finish in the proposed time, they would earn a rare stone **(game element Rarity)**. The student would have the opportunity to exchange the item for more lives or items **(game element Economy)**
Social (SS)	This gamification design represents how a gamified educational system would provide social interaction. The student would have to join other students on a group mission, where they could help each other in order for everybody to reach the end **(game element Cooperation)**. The team which finishes first **(game element Competition)** would win the title "Pioneers" **(game element Reputation)**. Participants would be notified whenever other teams were close to reaching them **(game element Social pressure)**



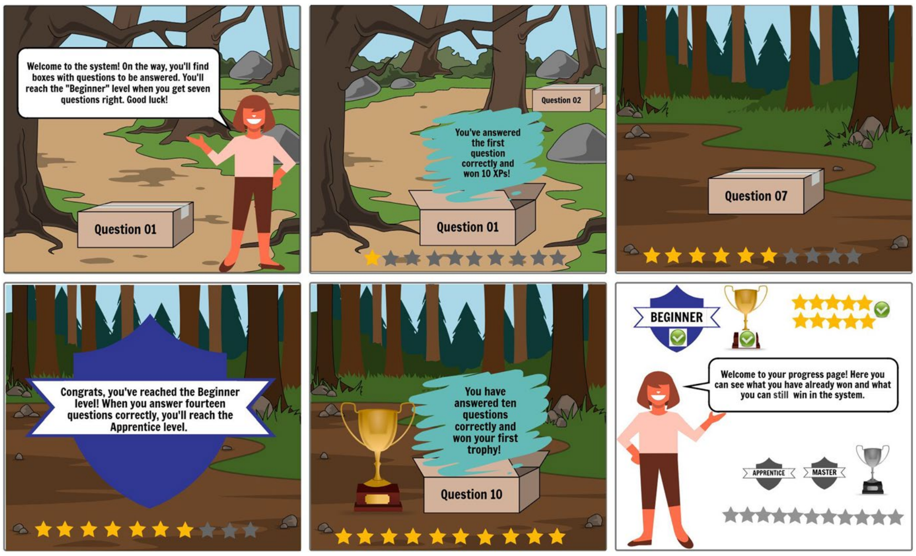
Frame 1: Imagine you're entering a system for the first time and hear an audio that says...; *Frame 2:* "A teacher was walking in a forest and filled the way with challenges, so as not to get lost on the way back. Are you able to unravel them to help her get home? You can create a profile or reply anonymously. What do you prefer?"; *Frame 3:* "If you chose to continue without creating a profile in the system, you can now start answering the questions"; *Frame 4:* "If you chose to create a profile, choose one avatar below."; *Frame 5:* "This will be your avatar in the system. You can post it on your social networks."; *Frame 6:* "Now you can start answering the questions. Good luck!"

Fig. 3 Storyboard fictional



Frame 1: Hello, welcome to our system! How about taking a tour to know the rules and icons of the system?; *Frame 2:* Your goal is to answer 21 questions correctly.; *Frame 3:* Every three correct questions you have the chance to answer a puzzle that will give you an extra life!; *Frame 4:* Don't worry! If you miss a question, you'll have the option to answer another question about the same topic and earn the lost point.; *Frame 5:* Every time the system has an update, you'll receive a notification when you log into the system. It can be auditory, visual, or vibration, according to your preferences. This way you won't miss any news! You can also propose improvements in the system.; *Frame 6:* Our tour is over. Now you can start answering the questions. Good luck!

Fig. 4 Storyboard personal

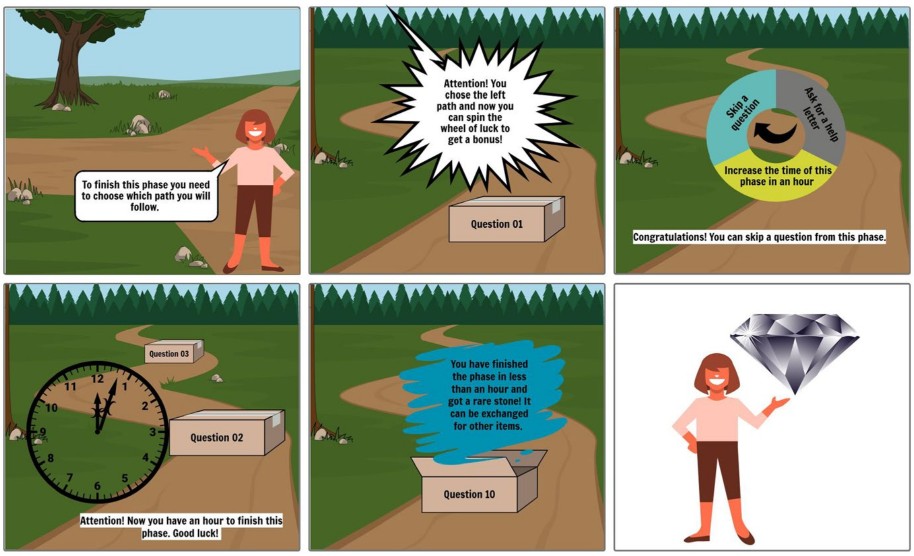


Frame 1: Welcome to the system! On the way, you'll find boxes with questions to be answered. You'll reach the "Beginner" level when you get seven questions right. Good luck!; *Frame 2:* You've answered the first question correctly and won 10 XPs!; *Frame 3:* -; *Frame 4:* Congrats, you've reached the Beginner level! When you answer fourteen questions correctly, you'll reach the Apprentice level.; *Frame 5:* You have answered ten questions correctly and won your first trophy!; *Frame 6:* Welcome to your progress page! Here you can see what you have already won and what you can still win in the system.

Fig. 5 Storyboard performance

Frame 1: Hello! This phase is a group challenge. Júlia and John are on this mission with you. You need to answer five questions correctly to finish the mission.; *Frame 2:* Attention! John is in trouble and if he doesn't finish question three, the group won't finish the mission. Do you want to send a help letter to John?; *Frame 3:* John answered question three correctly! Just two more questions and you'll finish the mission!; *Frame 4:* Group, attention! There are two other groups finishing the fourth question and they can surpass you in the challenge.; *Frame 5:* Congratulations team! You are the first team to finish the challenge and have won first place in the class!; *Frame 6:* This is the title that the group received for finishing in first place.

Fig. 6 Storyboard social



Frame 1: To finish this phase you need to choose which path you will follow.; *Frame 2:* Attention! You chose the left path and now you can spin the wheel of luck to get a bonus!; *Frame 3:* Congratulations! You can skip a question from this phase.; *Frame 4:* Attention! Now you have an hour to finish this phase. Good luck!; *Frame 5:* You have finished the phase in less than an hour and got a rare stone! It can be exchanged for other items.; *Frame 6:* - .

Fig. 7 Storyboard ecological

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Author Contributions ACGS took part in conceptualization, methodology, investigation, data curation, formal analysis, writing—original draft. WO involved in conceptualization, methodology, supervision, formal analysis, validation, writing—review & editing. JH participated in supervision, validation, formal analysis, writing—review & editing. LR involved in writing—review. AMT participated in writing—review. PTP took part in writing—review. SI involved in supervision, writing—review.

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Data availability Original dataset available as supplementary material.

Declarations

Conflict of interest This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue. The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

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APPENDIX

C

PSYCHOMETRIC INVESTIGATION OF THE HEXAD SCALE IN BRAZILIAN PORTUGUESE

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Psychometric investigation of the gamification Hexad user types scale in Brazilian Portuguese

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Gamification has become a significant direction in designing technologies, services, products, organizational structures, and any human activities towards being more game-like and consequently being more engaging and motivating. Albeit its success, research indicates that personal differences exist with regards to susceptibility to gamification at large as well as to different types of gamification designs. As a response, models and measurement instruments of user types when it comes to gamification have been developed. One of the most discussed related instruments is the Hexad user types scale. However, there has been paucity of research related to the validity and reliability of the Hexad instrument in general but also of its different formulations and language versions. To face this gap, our study focused on analyzing the psychometric properties of the Hexad scale in Brazilian Portuguese by conducting two confirmatory factor analyses and two multi-group confirmatory factor analyses. The survey was answered by 421 Brazilian respondents (52% self-reported women, 47% self-reported men, 0.5% preferred not to provide their gender, and 0.5% checked the option "other"), from the five Brazilian regions (23 different states and the Federal District), and aged between 10 and 60 years old. Findings support the structural validity of the scale as an oblique model and indicate opportunities for small improvements. Further research, both at academy and practice, may use this study as the source of measurement of user types related to gamification (in Brazilian Portuguese), as well as, as a theoretical and practical source for further studies discussing personalized gamification.

Gamification refers to transforming systems, services, and activities to better afford similar motivational benefits as games often do[1]. It has been used across a wide range of human activities ranging from education to well-being[2–4], to improve users' experience and engagement[4]. After its introduction as an own research field roughly a decade ago, researchers primarily investigated *whether* gamification works[5]. Although these investigations showed that gamification leads to positive outcomes in most cases, also neutral or even negative outcomes have been reported[3,5,6]. This prompted gamification research to focus on understanding *how* and *why* it works (or not)[2]. It was found that interpersonal differences exist in the perception of gamification elements, making personalization, i.e. adapting gamified systems to the individual user, an important topic in the field[4].

Past research has shown that personality traits or demographic factors like age or gender play a role in how gamification elements are perceived[4]. However, none of the aforementioned factors are particularly suitable for personalizing gamified systems, which is why there was a need for a dedicated theoretical model focusing on explaining inter-personal gamification preferences. The Hexad user types model, which was introduced by Marczewski[7], satisfies this need. The Hexad is, as far we know, the only available user trait model which was specifically developed for the context of gamification (rather than games)[8] and has been empirically validated by Tondello *et al.* in 2019[9]. Despite being recent, the Hexad has been used widely to tailor gamified systems to the user[4] and has been shown to be superior in explaining user preferences for gamified systems compared to personality traits and other player typologies[10]. The model is based on Self-Determination Theory[11], a major theory of human motivation, and consists of six user types which differ in the degree to which they are driven by intrinsic and extrinsic motivations: *Achievers* (motivated by mastery), *Players* (driven by extrinsic rewards), *Socialisers* (appreciating social interaction), *Philanthropists* (motivated by purpose), *Free-Spirits* (driven by exploration) and *Disruptors* (who like to trigger change).

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The Hexad user types scale (composed of 24 non-invasive items) to access these user types was initially created in English[12], and since its development, has been validated in different languages. Akgün and Topal[13] conducted a study where they adapted this first version of the scale[12] into Turkish. After presenting weak load values and a high error rate in the confirmatory factor analysis (CFA), two items (one from Player and another from Disruptor sub-scale) were removed from the final scale in Turkish. The study conducted by Tondello *et al.*[9] was the first study validating the scale in English and Spanish, presenting new items and also indicating the necessity to validate this new version in other languages. Taşkın and Çakmak[14] using the Single-Translation Method and focusing on the meaning rather than verbatim, conducted a study to adapt this new validated scale[9] into Turkish. More recently, Krath and von Korflesch[15] conducted a study to investigate the relationship between user types and game elements preferences, where they also conducted a validation of the Hexad scale in English and German. They indicated that even though the instrument was adequate in both language validations to identify the user types, both scales needed improvements to achieve a better model fit.

Also, two different studies focused on the validation of the scale specifically to adolescents, Ooge *et al.*[16] conducted a validation process of the Hexad scale in Dutch and Manzano-León *et al.*[17] in Spanish. In the validation in Dutch with adolescents, Ooge *et al.*[16] were not able to confirm the validity of the scale, showing that the scale may not be suitable for adolescents. They proposed a further investigation about the scale and also a simplification of some items, becoming closer to the adolescents' language. On the other hand, the study conducted by Manzano-León *et al.*[17] was able to validate the scale in Spanish with adolescents, and also has shown that the instrument can be used regardless of gender (*i.e.*, boys and girls understood the scale in the same way).

Although these validation studies provided different versions of the scale, missing validated translations of the instrument prevent its use among other non-native speakers. As a consequence, albeit its proven scientific and practical value, researchers and practitioners in many countries cannot make use of the Hexad scale. In the study to validate the scale in English and Spanish, Tondello *et al.*[9] tried to validate the scale in Brazilian Portuguese, however, they did not collect enough answers to conduct statistical analyses. In this article, we contribute to this issue by analyzing the psychometric properties of the Hexad scale in Brazilian Portuguese, a language spoken by more than 211 million native speakers, of which only 5,1% of the population have good English comprehension skills[18]. Consequently, we enable researchers to both recruit from a larger and thus potentially more representative pool of participants as well as increase the scientific validity of studies incorporating the Hexad scale in this language.

As far as we know, our study is the first to analyze the psychometric properties of the Hexad scale[9] in Brazilian Portuguese. We report findings from an online study with 421 participants, in which we analyzed the reliability and validity of the translated instrument, by conducting two CFA. We also conducted two Multi-group Confirmatory Factor Analysis (MGCFA) to confirm that men and women understood the instrument in the same way, and analyzed the correlations between the Hexad user types. Our results support the structural validity of the translated scale as an oblique model (*i.e.*, with correlations between sub-scales) and indicate that 22 of the 24 items have an acceptable internal consistency. We also identified that there are opportunities for improvement in the future.

Method

In this study, our goal was to analyze the psychometric properties of the gamification Hexad scale proposed by Tondello *et al.*[9] (originally in English and Spanish) in Brazilian Portuguese. Initially, the survey was presented to the respondents as an online survey through the platform Google Forms, consisting of two sections: (i) demographic data (age, gender (male, female, other, and I prefer to not inform), educational level, state (Brazil has five large geographic regions, with 26 states and one Federal District)), and gaming habits (if the respondent play games and the frequency (every day, every week, rarely, and I do not know)), and (ii) the Hexad scale (composed of 24 statements, four items for each sub-scale). The Hexad scale items were presented on a 7-point Likert scale[19], as recommended in the original study[9]. To avoid responses from people who did not pay due attention when reading and answering the statements, following other studies in the area[8,10], we inserted an "attention-check" statement (*i.e.*, "I like to be with my friends, but this question is just to evaluate your attention. Please, mark option number 3, to let us know that you are paying attention"). This "attention-check" statement was in the middle of section two (i.e., the Hexad scale), and similar to the Hexad items, was presented on a 7-point Likert scale. Responses from people who missed the attention-check statement were removed from the data analysis. In addition, the 24 items of the Hexad scale were presented to participants in a random order, as recommended by Tondello *et al.*[12].

The 24 items of the Hexad scale were the items available (in Portuguese) on the website of the HCI Games Group. According to Tondello *et al.*[9], two independent native speakers separately translated all the statements and descriptions into Brazilian Portuguese from the original version. Besides, each item was compared and assessed by an independent third native speaker. The original scale (in English) and the scale used in the study, can be seen in supplementary Table S1. After the survey construction and before the official survey release, as recommended by Connelly[20], two researchers conducted a pilot study by applying the survey to 10 people where they evaluated the size of the survey. The participation in this pilot study was voluntary, the respondents also had to pass in the "attention-check" statement, and eight of the ten participants evaluated the survey size as adequate.

Participants. Two researchers conducted the data collection. Aiming to have participants with different backgrounds, participants were recruited via email lists (academic and non-academic) and social networks (Facebook, Instagram, and Twitter) between March and October of 2020. The email lists were from personal contacts of the researchers, from participants of previous researches and also from participants that made available their emails in a conference of educational technology organized by one of the researchers. The propagation through Twitter, Facebook, and Instagram was made in the researchers' personal accounts, and in the propagation in Facebook, the researchers also posted about the research in public groups about gamification. All the postings in social networks were not targeted at any kind of ads and the publications were made public to facilitate the propagation by others. Considering that volunteers might be more willing to pay attention in surveys and also without pressuring to maximize time usage[21], participation in the study was entirely voluntary. Participants had to accept to participate by checking a consent term, where they were informed about the purpose of the study, the study confidentiality, that the data collected would be used in scientific studies, and also the contact of the researchers and universities involved in the study. Similar to the original study, participants could quit the study at any time before submitting responses.

463 responses were collected, of which 42 were discarded for having missed the attention-check item. With that, we analyzed data from 421 participants (219 women, 198 men, two participants preferred not to provide their gender, and two reported themselves as "other"). We received responses from 23 Brazilian states and the Federal District, covering the five geographic regions of Brazil. Besides, the number of participants in our study (N = 421) can be considered acceptable for CFA and multi-group CFA (MGCFA) by gender, since different authors have indicated as recommendations regarding the minimum necessary sample size in factor analysis a sample of at least 100, with a sample of 200 being considered fair, and a sample of 300 being considered a good sample[22,23]. Most of the respondents had at least a bachelor degree (Elementary/Middle/High School = 10%; Bachelor = 32%; Specialized/MBA Courses = 21%; M.Sc. = 24%; PhD = 13%), and were older than 20 years (10 to 19 = 9%; 20 to 29 = 29%; 30 to 39 = 28%; 40 to 49 = 23%; 50 to 59 = 10%; over 60 = 1%). Therefore, we were able to collect data from people with different demographic backgrounds. Also, most of the respondents (68%) reported that playing games were a habit.

Statistical analysis. We analyzed the (i) descriptive statistics, (ii) internal reliability, (iii) correlation between user types, and (iv) factor analysis of the data. As the aim of the study was to assess the psychometric properties of a model (Hexad scale), according to Levine[24] a CFA is a more appropriate procedure in comparison with an EFA. Similar to Manzano-León *et al.*[17], we also conducted two MGCFA aiming to analyze gender invariance (*i.e.*, to assess whether the survey is understood in the same way by men and women).

The data were analyzed using IBM SPSS 27[25] and JASP 0.14.1[26]. We used the software IBM SPSS 27[25] to conduct a Kolmogorov-Smirnov test (aiming to see if the data was parametric or non-parametric), to measure the descriptive statistics (mean, the standard deviation, and the data variances in each sub-scale), the internal reliability (Cronbach's α), and the bivariate correlation coefficients (Kendall's τ) in the data obtained. We also used this software to conduct a Wilcoxon test[27], to see if there was a significant difference between the answers based on the genders and a Friedmans test[28] with Bonferroni adjustment to test the difference between the user types.

We used the software JASP 0.14.1[26] to conduct the CFA, using structural equation modeling (SEM) with a robust maximum likelihood method. Considering that the Kolmogorov-Smirnov test showed that our data were non-parametric, we used the robust option of the method as it is more suitable for analyzing data that does not follow a normal distribution[29]. To assess the model fit, we analyzed the Chi-Square (χ^2), the Relative Chi-square (χ^2/df), the Goodness of Fit Index (GFI), the Tucker-Lewis Index (TLI), the Comparative Fit Index (CFI), the Bentler-Bonett Normed Fit Index (NFI), the Standardized Root Mean Square Residuals (SRMR) and the Root Mean Square Error of Approximation (RMSEA) results. Based on different studies' recommendations[30–34] we considered the goodness-of-fit indexes as χ^2 p ≥ 0.05; $\chi^2/df \leq 3$; GFI ≥ 0.95; TLI ≥ 0.95; CFI ≥ 0.95; NFI ≥ 0.95; SRMR ≤ 0.08; and RMSEA ≤ 0.06.

Since prior research about the Hexad scale conducted different CFA (considering an orthogonal model or an oblique model), we conducted two different CFA. In the first one, the factors were not correlated, therefore, the six Hexad user types were modeled as latent variables, the 24 survey items were modeled as observed variables, and the four items associated with each user type modeled as reflections of the respective latent variable. The second CFA was conducted correlating the factors, with the six Hexad user types modeled as latent variables correlated with each other, the 24 survey items modeled as observed variables, and the four items associated with each user type modeled as reflections of the respective latent variable.

We carried out two MGCFA (one considering an orthogonal model and another considering an oblique model), to confirm whether the factor structure of the scale is invariant according to the gender of the respondent (i.e. women and men understood the scale in the same way). In this analysis, we only considered the data from respondents that self-reported their gender as male or female (417 answers from the 421 answers collected). The analysis was carried out in the software JASP 0.14.1[26], using the robust maximum likelihood method, and evaluating the invariance of three models (unconstrained, metric, and scalar). The first model (unconstrained model) evaluated whether the number of items and factors were acceptable for both genders, the second model (metric invariance) analyzed whether the factor loadings of the items could be considered equivalent between the genders, and the third model (scalar invariance) investigated whether the level of latent trait needed to endorse the item categories (thresholds) was equivalent between the genders. To the evaluation of the model, we considered as goodness-of-fit indexes: RMSEA ≤ 0.06, SRMR ≤ 0.08, CFI ≥ 0.95, and TLI ≥ 0.95[30,35]. The invariance was evaluated using the CFI difference test (ΔCFI). When the difference between the ΔCFI of the models is under 0.01, the results indicate the invariance of the model[36].

Results

In this section, we present the results from the analyses of internal reliability, distribution of the Hexad user types, correlations presented between the user types, and the results from the confirmatory factor analyses and gender invariance.

Internal reliability, correlations and user type distribution. Initially, we analyzed the distributions of the responses for all variables by using Kolmogorov-Smirnov test[37], which results showed that the scores from all the variables were not normally distributed. We also measured the descriptive statistics (Mean, the standard deviation, and the data variances in each sub-scale), the internal reliability analyses (Cronbach's α), as well as the bivariate correlation coefficients (using Kendall's τ). Supplementary Table S2 presents the results. Considering that each Hexad sub-scale has four items rated on a 7 point Likert-scale, the minimum value a sub-scale can be is 4 and the maximum value a sub-scale can be is 28. Overall, the reliability scores are acceptable ($\alpha \geq 0.70$), except for the Disruptor sub-scale. Prior studies[9,16] have also found similar results ($\alpha \leq 0.70$) for the Disruptor sub-scale. Since the user type scores were non-parametric, as recommended by Wohlin *et al.*[38], we measured the bivariate correlation coefficients between each Hexad user type using Kendall's τ. In our study, similar to Tondello *et al.*[9], we identified a partial overlap between the user types, however in different levels.

As reported in supplementary Table S2, the higher average scores were from Philanthropists, Achievers, and Free Spirits, and the lower average scores were from Disruptors. These values are similar to other recent studies about the Hexad user types[9,14,17,39]. We also calculated the dominant user types (*i.e.* the strongest tendency of the respondents[10,40]), which distribution results were: Philanthropist = 34%, Achiever = 30%, Free Spirit = 13%, Player = 12%, Socialiser = 11%, and Disruptor = 1%. Philanthropists, Achievers, and Free Spirits were the dominant user types of 77% of the respondents, which were expected considering that the respondents presented higher average scores in these three user types. When considering gender, the distribution of the participants who self-reported as female was: Philanthropist = 35%, Achiever = 26%, Free Spirit = 14%, Player = 10%, Socialiser = 13%, and Disruptor = 1%, while the distribution of the participants who self-reported as male was Philanthropist = 32%, Achiever = 35%, Free Spirit = 10%, Player = 14%, Socialiser = 8%, and Disruptor = 1%. Therefore, there were more Philanthropists, Free Spirits, and Socialisers between the self-reported women, while the self-reported men presented a higher percentage of Achievers and Players as dominant user types.

To analyze if there was a significant difference in the user types according to their gender, as our data are non-parametric and the variables (users types) are related, following Wohlin's *et al.*[38] orientations, we conducted the Wilcoxon test[27]. The results show that there was no significant difference between the genders. We also tested the difference between the groups (user types). As our data are non-parametric and the variables are related, following Wohlin's *et al.*[38] recommendations, we conducted the Friedmans test[28] with Bonferroni adjustment, thus, reducing the chance of Type-I errors[41]. The overall results ($\chi^2_5 = 915.834$, $p \leq 0.000$) demonstrated a significant difference between the groups. The adjusted results indicate a difference between all of the groups, with an exception for Socialisers and Players, and Achievers and Philanthropists.

Confirmatory factor analysis. When analyzing the path models of the studies that tried to validate the Hexad scale, it was possible to find two different approaches in the conduction of the CFA. While the studies conducted by Tondello *et al.*[9] and by Ooge *et al.*[16] considered the Hexad as an orthogonal model (*i.e.*, the six user types as factors without correlation between them), Akgün and Topal[13], Taşkın and Çakmak[14], and Manzano-León *et al.*[17] considered the Hexad model as an oblique model (*i.e.*, the six user types as factors correlated to each other). Initially, we decided to replicate the CFA conducted by Tondello *et al.*[9] and Ooge *et al.*[16],i.e., considering the six user types as factors without correlation between them. Figure 1 presents the path model.

To evaluate the goodness of fit of the model, following Kline's[42] suggestion, we initially used the chi-squared test χ^2 and the root mean square error of approximation (RMSEA). The Chi-squared test did not support the evidence for a good model fit ($\chi^2_{252} = 1910.204$, $p \leq 0.001$). However, the Chi-squared test is sensitive to the sample size, normally rejecting the model fit when large samples are used and not discriminating good fitting models and poor fitting models when small samples are used[30]. Thus, we calculated the $\chi^2/df = 3.6$, which did not indicate a good model fit, however, indicated a fair fit[30,43]. The RMSEA = 0,125 (CI = [0.120, 0.130]) also did not support the evidences for a well-accepted fitted model[32]. The Comparative Fit Index (CFI) = 0.702, the Tucker-Lewis Index (TLI) = 0.673, the Bentler-Bonett Normed Fit Index (NFI) = 0.673, and the Standardized root mean square residual (SRMR) = 0.314 also did not indicate an acceptable fit of the model[30,32]. However, the Goodness of fit index (GFI) = 0.956, indicated a good fit[33].

Table 1 present the factor loadings for each of the Hexad survey items in Brazilian Portuguese. Since Cronbach's α may be misleading due to its tendency to underestimate reliability[44], the composite reliability (CR) is a good option to measure the reliability considering that is formulated through structural equation modeling and is equivalent to coefficient omega[45]. Based on these factor loadings, we calculated the composite reliability (CR) finding acceptable values (CR $\geq$ 0.7) for all the factors except the Disruptor (Achiever = 0.874; Disruptor = 0.669; Free Spirit = 0.766; Philanthropist = 0.888; Player = 0.818; and Socialiser = 0.886).

In Table 2 we present the modification indices with values $\geq$ than 30.000. The modification index is an approximation of how much each parameter could decrease the χ^2 value, and therefore, improve the fit model, if freely estimated[35,42]. The expected parameter change (EPC) indicates an estimation of how much the parameter would change if freely estimated[35]. The results indicated that especially the item D2 has presented a correlation with all the factors, which indicates that possibly an improvement in this item would improve the model fit.

In summary, when using a similar path model that Tondello *et al.*[9] and Ooge *et al.*[16] studies used, CFA demonstrated that the measurement model has not an acceptable fit considering our data, indicating that some items could be improved. One of the possible explanations for this result is that probably occurred an overlap of items measuring the same factor. The results demonstrated that items D2 and F2 were the weaker fit to their respective sub-scales (see Table 1).

After analyzing the results from Kendall's test (that indicated correlation between the user types) as well as the results from the first CFA (that indicated a poor fit model), we decided to conduct a second CFA considering

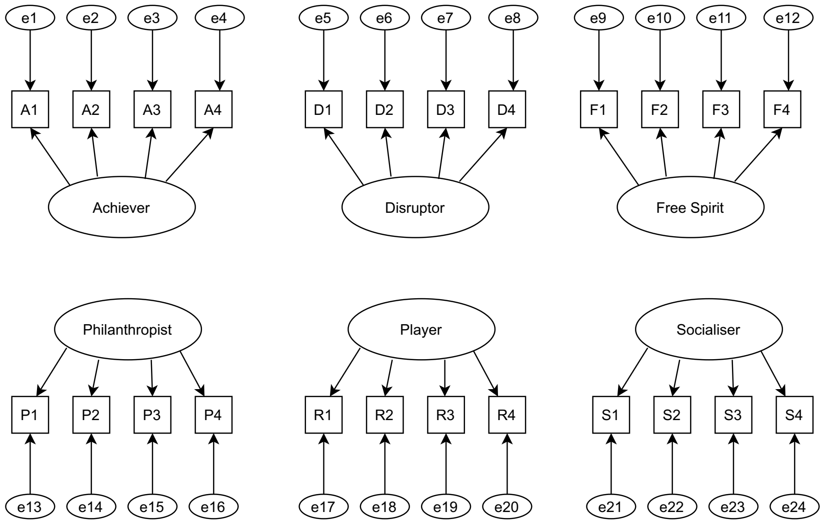

Figure 1. Path model (adapted from Tondello *et al.*[9]). The ellipses represent the factors and the rectangles represent the items of the scale.

				CI		
UT	**I**	**SE**	**Z-value**	**5%**	**95%**	**λ**
A	**A1**	0.087	12.141	0.884	1.225	**0.836**
	A2	0.077	15.827	1.075	1.378	**0.790**
	A3	0.089	11.866	0.879	1.227	**0.779**
	A4	0.086	12.574	0.912	1.248	**0.779**
D	**D1**	0.105	9.822	0.825	1.237	**0.539**
	D2	0.109	7.890	0.645	1.072	0.491
	D3	0.106	11.758	1.035	1.449	**0.648**
	D4	0.099	11.950	0.985	1.371	**0.636**
F	**F1**	0.092	12.509	0.969	1.329	**0.793**
	F2	0.095	8.582	0.629	1.001	0.496
	F3	0.090	12.100	0.914	1.268	**0.807**
	F4	0.098	9.450	0.731	1.113	**0.560**
P	**P1**	0.081	13.543	0.940	1.258	**0.868**
	P2	0.073	16.172	1.042	1.329	**0.851**
	P3	0.083	13.072	0.926	1.252	**0.799**
	P4	0.089	11.585	0.856	1.205	**0.737**
R	**R1**	0.086	15.317	1.145	1.481	**0.694**
	R2	0.075	18.568	1.240	1.533	**0.855**
	R3	0.088	11.556	0.846	1.192	**0.640**
	R4	0.089	14.663	1.131	1.480	**0.712**
S	**S1**	0.069	19.810	1.224	1.493	**0.823**
	S2	0.063	23.211	1.332	1.577	**0.908**
	S3	0.075	16.355	1.087	1.382	**0.721**
	S4	0.068	19.214	1.165	1.430	**0.789**

Table 1. Factor loadings. $N = 421$. UT: User types/factors; I: Items; SE: standard errors; CR: critical ratios; CI: Confidence interval; λ: standardized λ; bold: $\lambda \geq 0.500$; A: Achiever; D: Disruptor; F: Free Spirit; P: Philanthropist; R: Player; S: Socialiser.

	Modification Indices	Expected Parameter Change
Achiever → D2	111.430	0.884
Free Spirit → D2	98.619	0.864
Philanthropist → D2	88.796	0.781
Free Spirit → R3	76.296	0.613
Socialiser → D2	62.360	0.651
Socialiser → F4	49.211	0.512
Philanthropist → R3	47.072	0.458
Achiever → R3	46.979	0.463
Player → D2	37.588	0.524
Philanthropist → A1	35.505	0.252

Table 2. Modification indices of the first CFA. $N = 421$.

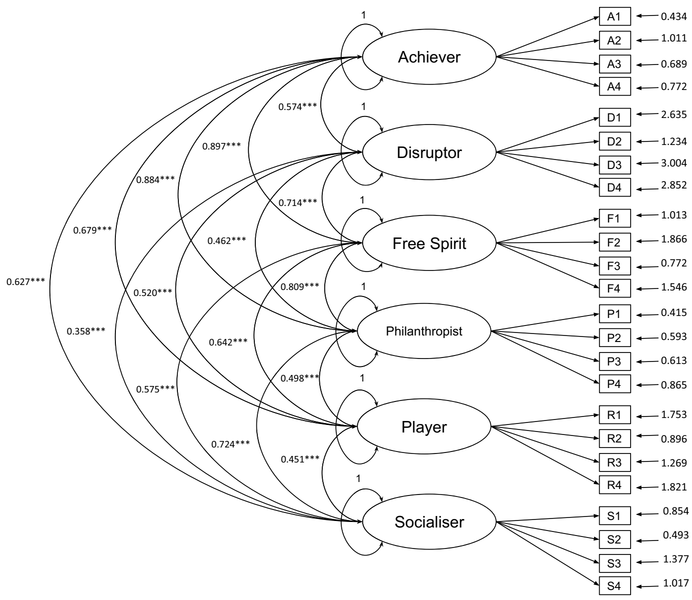

Figure 2. Path model with correlations between the factors. The ellipses represent the factors and the rectangles represent the items of the scale. *** p < 0.001. The variance in each factor is defined in 1 by JASP[26]. All parameters were freely estimated in the analysis.

the six factors as correlated to each other. This CFA replicated the analysis conducted by Akgün and Topal[13], Taşn and Çakmak[14], and Manzano-León *et al.*[17]. Figure 2 presents the path model.

The Chi-squared test did not support the evidence for a good model fit ($\chi^2_{252} = 646.836$, $p \leq 0.001$), however, differently from the first CFA, the $\chi^2/df = 2.56$, the RMSEA = 0.064 (CI = [0.058, 0.070]), and Standardized root mean square residual (SRMR) = 0.073, indicated a good fit[30]. The Comparative Fit Index (CFI) = 0.926, the Tucker-Lewis Index (TLI) = 0.914, the Bentler-Bonett Normed Fit Index (NFI) = 0.889, and the Goodness of fit index (GFI) = 0.882 were slightly below the acceptable values that would indicate a good fit[30,32]. Thus, even though some of the indices did not indicate the good fit of the model to our data, when considering the Hexad as an oblique model, the indices were closer to indicating a good fit model than in the first CFA. Table 3 presents the factor loadings from this second CFA. We also calculated the CR based on these factor loadings, finding acceptable values (CR ≥ 0.7) for all the factors except the Disruptor (Achiever = 0.873; Disruptor = 0.622; Free Spirit = 0.769; Philanthropist = 0.888; Player = 0.819; and Socialiser = 0.886).

				CI		
UT	I	SE	Z-value	5%	95%	λ
A	A1	0.081	13.273	0.918	1.235	**0.853**
	A2	0.076	15.548	1034	1.332	**0.762**
	A3	0.084	12.735	0.902	1.230	**0.789**
	A4	0.081	13.313	0.915	1.231	**0.774**
D	D1	0.090	11.228	0.835	1.188	**0.529**
	D2	0.094	14.431	1.169	1.537	**0.773**
	D3	0.107	7.602	0.606	1.027	0.426
	D4	0.105	7.252	0.554	0.965	0.410
F	F1	0.087	12.030	0.873	1.213	**0.719**
	F2	0.084	10.891	0.747	1.074	**0.555**
	F3	0.086	11.887	0.858	1.197	**0.760**
	F4	0.072	14.995	0.936	1.218	**0.655**
P	P1	0.082	13.322	0.929	1.249	**0.861**
	P2	0.072	16.070	1.020	1.303	**0.833**
	P3	0.080	13.969	0.959	1.272	**0.818**
	P4	0.086	12.099	0.875	1.213	**0.747**
R	R1	0.081	16.783	1.193	1.509	**0.714**
	R2	0.066	19.851	1.186	1.446	**0.812**
	R3	0.083	13.559	0.964	1.290	**0.707**
	R4	0.085	14.536	1.073	1.407	**0.677**
S	S1	0.067	20.386	1.238	1.501	**0.829**
	S2	0.061	23.679	1.321	1.560	**0.899**
	S3	0.074	16.921	1.102	1.390	**0.728**
	S4	0.067	19.376	1.167	1.429	**0.790**

Table 3. Second factor loadings. $N = 421$. UT: User types/factors; I: Items; SE: standard errors; CR: critical ratios; CI: Confidence interval; λ: standardized λ; bold: $\lambda \geq 0.500$; A: Achiever; D: Disruptor; F: Free Spirit; P: Philanthropist; R: Player; S: Socialiser.

	Modification indices	Expected parameter change
Free Spirit → D2	106.398	2.348
Achiever → D2	88.736	1.508
Philanthropist → D2	77.717	1.133
Free Spirit → R3	69.735	0.837
Achiever → R3	49.527	0.710
Socialiser → D2	43.896	0.738
Philanthropist → R3	41.049	0.515
Achiever → D4	39.436	−0.801
Philanthropist → D4	34.883	−0.655
Achiever → D3	32.154	−0.749
Free Spirit → D4	31.378	−0.928

Table 4. Second modification indices of the second CFA. $N = 421$.

In Table 4 we present the modification indices with values ≥ than 30.000. Again, the item D2 presented a correlation with most of the factors, however, in this analysis, the items D3 and D4 also presented some correlations with the factors. This might indicate the necessity of improvement in all the Disruptor sub-scale items.

When modeling the path model similar to Akgün and Topal[13], Taşn and Çakmak[14], and Manzano-León *et al.*[17] studies, CFA results demonstrated that the model is closer to an acceptable fit but also can be improved. In this analysis, the items D3 and D4 were the weaker fit to the Disruptor sub-scale (see Table 3). After this CFA analysis and also considering the analysis made by Akgün and Topal[13], Taşn and Çakmak[14], and Manzano-León *et al.*[17] studies, we understand that the Hexad is an oblique model, and that is why it presents a better fit model when correlating the items in the CFA.

Gender invariance analysis. To measure the gender invariance, we carried out two MGCFA (one considering the orthogonal model and another considering the oblique model). In the first MGCFA (orthogonal model), the comparisons between the unconstrained model (RMSEA = 0.130 [0.124–0.135]; SRMR = 0.321; TLI = 0.655; CFI = 0.685), the metric invariance (RMSEA = 0.128 [0.122–0.133]; SRMR = 0.321; TLI = 0.666; CFI = 0.684; Δ CFI = −0.001), and the scalar invariance (RMSEA = 0.127 [0.121–0.132]; SRMR = 0.309; TLI = 0.671; CFI = 0.678; Δ CFI = −0.006), indicated an acceptable invariance (ΔCFI $\leq$ 0.01).

In the second MGCFA (oblique model), the comparisons between the unconstrained model (RMSEA = 0.123 [0.118–0.129]; SRMR = 0.097; TLI = 0.688; CFI = 0.715), the metric invariance (RMSEA = 0.121 [0.116–0.126]; SRMR = 0.103; TLI = 0.700; CFI = 0.684; Δ CFI = −0.001), and the scalar invariance (RMSEA = 0.120 [0.115–0.125]; SRMR = 0.101; TLI = 0.705; CFI = 0.706; Δ CFI = -0.008) also indicated an acceptable invariance (ΔCFI $\leq$ 0.01). Therefore, the results of both MGCFA demonstrated that the instrument in Brazilian Portuguese can be used regardless of gender, independent of model.

Discussion

In this study, we focused on analyzing the psychometric properties of the Hexad user types scale[9] in Brazilian Portuguese. To do so, we administered the so far non-validated Brazilian Portuguese version to 421 Brazilian respondents. Considering studies that validated the Hexad scale in other languages, we carried out reliability analysis, two different confirmatory factor analyses (CFA), and two multi-group confirmatory factor analyses (MGCFA) in our data set. Concerning the CFA, the CFA considering the Hexad an oblique model presented a closer good model fit, which might indicate that the best way to conduct CFA in the Hexad scale is assuming correlations between the six factors. However, both CFA indicated problems with the Disruptor sub-scale. The MGCFA indicated that the instrument can be used regardless of gender.

Considering the distribution of the scores, our results are similar to prior research[9,14,17,39], demonstrating that Philanthropists, Achievers, and Free Spirits are the strongest tendencies of the users regarding the Hexad user types, while Disruptor is the lower tendency. We also calculated the dominant user types, indicating that Achiever and Philanthropist were responsible for more than 60% of the dominant user types of the respondents. Partially similar to the results found by Tondello *et al.*[9], participants who self-reported as female, seemed to be more motivated by the Philanthropist, Free Spirit, and Socialiser tendencies while participants who self-reported as male, seemed to be more motivated by the Achiever and Player tendencies. The results from the study conducted by Oyibo *et al.*[46], which indicated that male participants are more responsive to rewards strategies, might explain why they are more motivated by the Player user type.

Our results presented significant correlations between the user types, which some were expected taking into account that their underlying motivations are related[12]. The strongest correlation occurred between Philanthropists and Socialisers, and could be expected since both user types are interested in social interaction, with Socialisers interested in the interaction itself and Philanthropists interested in interaction for altruistic purposes[9]. These correlations between the user types might complicate the creation of items that only fit one user type, and also, we understand that these correlations between the user types are a theoretical indication that the Hexad is an oblique model.

In the first CFA, when not correlating the factors, our study did not present a good model fit (χ^2/df = 3.6, RMSEA = 0,125,CFI = 0.702, TLI = 0.673, NFI = 0.673, and SRMR = 0.314), and also two items presented $\lambda \leq$ 0.5 (D2: λ = 0.491, and F2: λ = 0.496). In our study, similar to Tondello *et al.*[9], the item F2 presented a low factor loading. Tondello *et al.*[9] indicated this item as passive of improvement, suggesting that it would probably fit better with another user type. Considering the problems that other studies presented with the Free Spirit sub-scale, and that the item F2 might be related with other user types[9,16], it is important to conduct future studies improving the sub-scale (specifically the item F2). Regarding the item D2, we think a possible problem with the item is the use of the Latin expression "status quo". In other validation studies, this expression was replaced by another expression in the validation language[9,14], or the respondents were informed about the meaning of the expression[16,17]. Therefore, we think that a reformulation of this item or a previous explanation about the expression "status quo" to the respondents, could improve the understanding and consequently, the results. In the CFA correlating the factors, the fit indices were acceptable or close to acceptable (χ^2/df = 2.56, RMSEA = 0.064, SRMR = 0.073, CFI = 0.926, TLI = 0.914, NFI = 0.889, and GFI = 0.882). Overall, the Disruptor sub-scale presented some problems (*i.e.*, items with $\lambda \leq 0.5$, Composite Reliability below the acceptable, and items presenting modification indices with values $\geq$ than 30.000), which we understand as an indication that a further investigation about this user type might be necessary to learn more about how people present its characteristics.

Similar to Manzano-León *et al.*[17], we also conducted MGCFA to assess whether gender could influence the understanding of the scale. Since we conducted two CFA, we decided to conduct two MGCFA (one correlating the factors and another not correlating the factors) to test the invariance of the scale. In both MGCFA, the invariance was evaluated using the CFI difference test (ΔCFI $\leq$ 0.01) indicating unconstrained, metric, and scalar invariance[36]. Albeit prior research has investigated how gender could affect the distribution of the Hexad user types[9,47], less is known about whether the same scale can be used for women and men. Analysis of how women and men understand the Hexad scale is important considering that gender can play an important role in gamification design[48,49]. Prior research has indicated that the preference for game elements can change depending on the gender[50–52], therefore, it is important to analyze if gender also has influence when defining the user type through a scale. Based on our results and the results presented by Manzano-León *et al.*[17], the Hexad scale is an instrument that can be used regardless of gender.

Overall, the different analyses conducted in this study demonstrated that the Brazilian Portuguese version of the Hexad scale is an instrument that is near to complete validation and can be used regardless of gender. The scale evaluated in this study can be used to identify the Hexad user types in future research involving Brazilian samples, at the same time that practitioners can use our results as a guide to modeling gamified systems according to the Hexad user types. The use of this translated instrument can be an effective option for researchers and practitioners to group people into different user types in a gamified context, and therefore, personalize gamified systems or conduct further analysis about user behavior and motivations on this type of system.

Limitations and opportunities for the future

This study has presented some limitations concerning different aspects. Considering the demographic information of the respondents, we were not able to collect answers in all Brazilian states, and also some regions had low participation, which prevented us to present possible correlations between the user types and demographic characteristics. Considering the age of the respondents, most of them were older than 20 years, therefore, the results here presented might not be applicable to children and teenagers. We analyzed the psychometric properties of the Hexad scale translated to Brazilian Portuguese, however, other countries also have Portuguese as the official language (*e.g.* Portugal, Angola, Mozambique), and the instrument used in this study might not be the most suitable to be used in these countries.

Based on these limitations, we propose some studies that can be carried out in the future. (i) Following other studies that tried to validate the scale for young people[16,17], we propose future studies specifically to analyze the psychometric properties the Brazilian Portuguese scale for adolescents. This validation with younger people can help designers to personalize gamified settings specifically developed for them (e.g. educational gamified environments for adolescents). (ii) Since there were items that did not reach the expected factor loading values in this study, future studies can propose new translations for them as well as new items to measure the Disruptor and Free Spirit sub-scale. These improvements can increase the reliability in these sub-scales and also the power of these items in the measurement of the Hexad user types. (iii) Finally, considering that the countries that have Portuguese as the official language present cultural differences and also some differences in the language itself, future studies can adapt the Brazilian Portuguese scale to other Portuguese-speaking countries, making possible the use of the scale in more locations.

Conclusion

Having models that identify the user types in gamified settings is a current challenge. Although there is already a scale to measure the users' profile considering gamification aspects (*i.e.*, Hexad), this has not yet been validated in several widely spoken languages (*e.g.*, Brazilian Portuguese), failing to benefit a large number of researchers and practitioners. In this study, we analyzed the psychometric properties of the Hexad scale in Brazilian Portuguese. Our results demonstrated that the Brazilian Portuguese version has good internal reliability, CFA values acceptable or near to the acceptable (needing special attention the Disruptor sub-scale), and that there were overlaps between the user types. These overlaps between the user types as well as the statistical results when modeling the CFA with correlated factors indicate that the best way to conduct CFA of the Hexad scale in the future is considering the Hexad as an oblique model. The study results indicated that the model is close to complete validation, but some items still need to be improved. As future studies, we intend to analyze and adapt the items that presented a low factor loading and then replicate the study with new participants. We also aim to adapt and analyze the psychometric properties of the scale in Portuguese from other Portuguese-speaking countries. Other studies improving the scale could help a considerable number of researchers that conduct studies with Brazilian respondents. Having a validated Hexad scale in Brazilian Portuguese can represent a significant advance in identifying the profile of the users and, consequently, in the personalization of several types of gamified systems.

Ethical statements. This study has been performed in accordance to the Brazilian National Health Council resolution number 510 published on April 7th, 2016, and with the relevant guidelines and regulations set by the Universities involved. Informed consent for participation was obtained from all participants.

Data availability

The dataset generated and analyzed during the current study is available as supplementary material.

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Author contributions

A.C.G.S., W.O., and M.A. wrote the main manuscript text. J.H. was involved in the conceptualization of the study and was responsible for the writing review and editing of the manuscript text. S.I. was involved in the conceptualization of the study. A.C.G.S. and W.O. were involved in the conceptualization of the study, the design of the study, the data collection, and prepared the figures and tables. A.C.G.S., W.O., and J.H. were responsible for the data analysis and data interpretation. W.O. and J.H. were responsible for the supervision. All authors approved this current version.

Competing interests

The authors declare no competing interests.

Additional information

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		English items	Brazilian Portuguese items
Philanthropist	P1	It makes me happy if I am able to help others.	Sinto-me feliz se sou capaz de ajudar os outros.
	P2	I like helping others to orient themselves in new situations.	Gosto de ajudar os outros a se orientarem em situações novas.
	P3	I like sharing my knowledge.	Gosto de compartilhar meu conhecimento com os outros.
	P4	The well-being of others is important to me.	O bem-estar dos demais é importante para mim.
Socialiser	S1	Interacting with others is important to me.	Interagir com os demais é importante para mim.
	S2	I like being part of a team.	Gosto de fazer parte de uma equipe.
	S3	It is important to me to feel like I am part of a community.	É importante para mim sentir que faço parte de uma comunidade.
	S4	I enjoy group activities.	Gosto de atividades em grupo.
Free Spirit	F1	It is important to me to follow my own path.	É importante para mim seguir meu próprio caminho.
	F2*	I often let my curiosity guide me.	Frequentemente deixo-me guiar pela curiosidade.
	F3	Being independent is important to me.	Ser independente é importante para mim.
	F4	Opportunities for self-expression are important to me.	Considero importantes as oportunidades para expressar a mim mesmo.
Achiever	A1	I like defeating obstacles.	Gosto de superar obstáculos.
	A2	I like mastering difficult tasks.	Gosto de dominar tarefas difíceis.
	A3	It is important to me to continuously improve my skills.	É importante para mim aprimorar continuamente as minhas habilidades.
	A4	I enjoy emerging victorious out of difficult circumstances.	Gosto de sair vitorioso de circunstâncias difíceis.
Player	R1	I like competitions where a prize can be won.	Gosto de competições em que possa ganhar prêmios.
	R2	Rewards are a great way to motivate me.	Recompensas são uma ótima forma de me motivar.
	R3	Return of investment is important to me.	Retorno de investimento é importante para mim.
	R4	If the reward is sufficient I will put in the effort.	Se a recompensa for suficiente, farei o esforço.
Disruptor	D1	I like to provoke.	Gosto de provocar.
	D2*	I like to question the status quo.	Gosto de questionar o status quo.
	D3**	I see myself as a rebel.	Vejo-me como um rebelde.
	D4**	I dislike following rules.	Não gosto de seguir regras.

Table S1. The original scale validated in English and the scale in Brazilian Portuguese. *: items that presented $\lambda \leq 0.500$ in the first CFA (orthogonal model, i.e., model that proposes uncorrelated factors); **: items that presented $\lambda \leq 0.500$ in the second CFA (oblique model, i.e., model that proposes correlated factors). <u>Instructions to use the scale:</u> to use the scale, ask the respondents on a 7-point Likert scale to rate how well each item describes them. Present the items randomly to guarantee that the respondent is not able to identify the items that are from the same sub-scale. To guarantee that the respondents are reading all the statements before providing an answer, include an “attention-check” item in the middle of the Hexad items. To calculate the user type, add the scores the user presented in each sub-scale. The user type is formed by the six scores from the scale, with the highest score as the dominant user type. <u>Instructions to use the scale (in Brazilian Portuguese):</u> *Para usar a escala peça aos respondentes que avaliem, em uma escala Likert de 7 pontos, o quão bem cada item da escala Hexad os descreve. Apresente os itens de forma aleatória, de modo que o respondente não consiga identificar quais são os itens de cada perfil de usuário. Para garantir que os respondentes estejam lendo inteiramente os itens, inclua um “item de atenção” entre os itens da escala Hexad. Para definir o perfil de usuário do respondente, some a pontuação de cada sub-scala. O perfil de usuário é formado pelas seis pontuações, com a maior pontuação sendo o perfil de usuário dominante.*

UT	M	SD	Var	α	A	*P-value*	D	*P-value*	F	*P-value*	P	*P-value*	R	*P-value*
A	23.90	4.733	22.401	0.871										
D	14.77	5.274	27.811	0.669	0.186**	0.000								
F	22.52	4.614	21.288	0.748	0.424**	0.000	0.310**	0.000						
P	24.18	4.681	21.909	0.885	0.464**	0.000	0.099**	0.005	0.372**	0.000				
R	20.63	5.572	31.052	0.812	0.377**	0.000	0.229**	0.000	0.337**	0.000	0.216**	0.000		
S	20.57	5.690	32.378	0.882	0.338**	0.000	0.087*	0.012	0.300**	0.000	0.483**	0.000	0.271**	0.000

Table S2. Descriptive analysis, internal reliability, and bivariate correlation coefficients (Kendall's τ) and significance between each Hexad user type and all others. N = 421. UT: User type; M: mean score; SD: standard deviation; Var: Variance; α: Cronbach's Alpha; A: Achiever; D: Disruptor; F: Free Spirit; P: Philanthropist; R: Player; S: Socialiser. ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

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